NBER WORKING PAPER SERIES

EXPECTATIONS, INFECTIONS, AND ECONOMIC ACTIVITY

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Working Paper 27988
http://www.nber.org/papers/w27988

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2020, Revised April 2022

A previous version of this paper was titled "How do People Respond to Small Probability Events with Large, Negative Consequences?" We thank Joao Guerreiro and Laura Murphy for excellent research assistance and Andrew Atkeson, Roberto Chang, Andy Neumeyer, and Venky Venkateswaran for their comments. Miguel Godinho de Matos was funded by the Portuguese Foundation for Science and Technology Grant UID/GES/00407/2013. The views expressed in this article are those of the authors and do not necessarily reflect the official views of authors' institutions, nor those of the National Bureau of Economic Research. The data we use is part of Statistics Portugal's project of making administrative data from the tax authority and other public agencies available for statistical production and research. See the Statistics Portugal website for information on how to access the data. Replication codes are available on the authors' websites.

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JEL No. E21,G51,I1

ABSTRACT

The Covid epidemic had a large impact on economic activity. In contrast, the dramatic decline in mortality from infectious diseases over the past 120 years had a small economic impact. We argue that people's response to successive Covid waves helps reconcile these two findings. Our analysis uses a unique administrative data set with anonymized monthly expenditures at the individual level that covers the first three Covid waves. Consumer expenditures fell by about the same amount in the first and third waves, even though the risk of getting infected was larger in the third wave. We find that people had pessimistic prior beliefs about the case-fatality rates that converged over time to the true case-fatality rates. Using a model where Covid is endemic, we show that the impact of Covid is small when people know the true case-fatality rate but large when people have empirically-plausible pessimistic prior beliefs about the case-fatality rate. These results reconcile the large economic impact of Covid with the small effect of the secular decline in mortality from infectious diseases estimated in the literature.

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1 Introduction

The Covid epidemic had a large impact on economic activity. In the U.S., the peak-to-trough decline in real GDP in the Covid recession is seven times larger than in the average pre-2008 recession and about three times larger than in the Great Recession (see Eichenbaum et al. (2022a)). In contrast, the dramatic decline in mortality from infectious diseases over the past 120 years had a small impact on economic activity.[1] For example, Acemoglu and Johnson (2007) argue that the large increases in life expectancy associated with lower mortality rates had a relatively small impact on per capita income.[2]

How can we reconcile the large economic impact of Covid with the small effect of the secular decline in mortality from infectious diseases? We argue that people's response to successive Covid waves provides an important clue to answering this question. Using administrative data from Portugal, we analyze the response of consumption expenditures to the three waves of Covid infections that peaked in April 2020, December 2020, and January 2021. Our key empirical finding is that consumer expenditures fell by about the same amount in the first and third waves, even though the risk of getting infected was much larger in the third wave. We also find that, across both waves, older consumers reduce their spending by more than younger consumers.

Standard models in which people know the actual case-fatality rate at the beginning of the epidemic cannot account for our key finding. These models imply that the drop in consumption should have been higher in the third wave. We argue that a model in which people have pessimistic beliefs about case-fatality rates and learn over time can account for the behavior of consumption expenditures by old and young in different Covid waves.

This argument underlies our explanation of why the economic impact of Covid was large, but the effect of the secular decline in mortality from infectious diseases was small. It is hard for people to initially estimate the health consequences of a once-in-a-century event like Covid. Because people had pessimistic prior beliefs about Covid case-fatality rates, they reduced consumption dramatically at the beginning of the epidemic. Our model-based estimates imply that people did learn about case-fatality rates by the third wave. This result suggests that people can estimate and internalize the health consequences of gradual, secular declines in mortality rates. As it turns out, a version of our model in which Covid is endemic

[1] See, e.g., Armstrong et al. (1999) and Hansen et al. (2016) for evidence on the decline of mortality rates.

[2] See also Bleakley (2018), who argues that the effect of lower mortality rates on income via an increased incentive to invest in human capital is relatively small.

implies that the steady-state effects of endemic Covid are small as long as people know Covid's true case-fatality rate. But those costs would be very large if people's perceptions of the case-fatality rate corresponded to those we estimate in the Portuguese data.

To formally establish our argument about the importance of expectations, we proceed as follows. We estimate a structural model in which old and young people are uncertain about case-fatality rates and update their beliefs using a parsimonious constant-gain learning algorithm. People of all ages can reduce the probability of becoming infected by cutting expenditures on goods and services that require social contact. We analyze people's consumption decisions using a partial-equilibrium approach. This approach 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. We estimate the key parameters of the model, including people's prior beliefs and the gain parameter, using a variant of the Bayesian procedure in Christiano et al. (2010), Christiano et al. (2016), and Fernández-Villaverde et al. (2016).

We find that people's belief about their case-fatality rate at the beginning of the epidemic greatly exceeds objective case-fatality rates.[3] The posterior mode of the gain parameter is large enough so that people's beliefs about their case-fatality rates essentially converge from above to their actual values by the beginning of the third wave. So, even though the probability of infection was much larger in the third wave than in the first wave, the actual decline in consumption expenditures is roughly the same in the two waves.

To help establish the importance of learning, we also estimate a version of the model in which people know their true case-fatality rates at the beginning of the epidemic. The performance of this version of the model, as measured by the marginal log-likelihood, is much worse than that of the learning model. This deterioration reflects the no-learning model's counterfactual prediction that the drop in consumption expenditures of young and old is larger in the third wave than in the first wave.

Our results suggest that the overall economic impact of Covid is small once people's beliefs about case-fatality rates have converged to their true values. To formally investigate this conjecture, we extend our partial-equilibrium model 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 as-

[3] This notion is consistent with is large literature that highlights the difficulties that people have in assessing and responding to low probability events (see, e.g. Slovic (2000) and Sunstein (2003)).

sumptions so that people who have natural immunity or are vaccinated lose their immunity over time. With this modification, Covid is endemic: there is a strictly positive fraction of the population that is infected in the steady state.

We compute the steady-state impact of Covid on economic activity under two scenarios. In the first scenario, we assume that people's beliefs about case-fatality rates are equal to the objective case-fatality rates. This assumption is natural given the large estimated value of the gain parameter of our partial-equilibrium model's learning algorithm and our focus on steady-state properties. Our key finding is that Covid reduces life expectancy at birth by 3.2 percent and reduces aggregate output by 1.1 percent relative to the pre-epidemic steady state. Taking sampling uncertainty into account, this effect is consistent with the Acemoglu and Johnson (2007)'s estimates of the impact of increases in life expectancy on real GDP.

In the second scenario, we assume that people's beliefs about case-fatality rates are equal to their prior beliefs at the beginning of the epidemic. Here, Covid has large steady-state effects on aggregate economic activity. Output falls by about 12 percent relative to the pre-epidemic steady state. These results reconcile the large economic impact of Covid with the small response to the secular decline in mortality from infectious diseases.

Our paper is organized as follows. Section 2 describes our data set. Section 3 contains our empirical results. Section 4 describes our partial-equilibrium model. Section 5 describes our estimation algorithm. Section 6 describes our empirical results. Section 7 discusses a general equilibrium model of endemic Covid. We conclude in section 8.

2 Data

Our dataset comes from Statistics Portugal (the national statistical authority). It covers the period from January 2018 to April 2021 and includes anonymized data 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 also 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.[4] We also compute individual pharmacy expenditures, which we use as a proxy for comorbidity.

Portuguese consumers have three incentives to include their fiscal number in expenditure receipts. First, they can then deduct from their income taxes expenditures on health, education, lodging, nursing homes, and general-household spending, up to a limit. 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 every ten euros of reported spending, consumers receive a coupon for a lottery in which the prize is a government bond with a face value of either 35 or 50 thousand euros.

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 from the sample all persons older than 80 because their expenditure patterns suggest that many of them live in nursing homes. We also exclude people younger than 20 years old 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.[5]

Table 1 reports descriptive statistics for monthly expenses net of VAT. For public servants,

[4]Our dataset does not include information on rent expenditures, mortgage, and other personal loan payments that are not subject to VAT.

[5]In 2011, Portugal entered into an adjustment program with the International Monetary Fund, the European Central Bank, and the European Commission (see Eichenbaum et al. (2017) for a discussion). The program called for annual reductions in the number of civil servants (one percent per year in the central government and two percent per year in the local and regional governments). This reduction led to a large increase in the number of retired public servants.

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 2 reports the same statistics as Table 1 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 3 displays case-fatality rates (the ratio of Covid deaths to people infected) by age cohort for Portugal. Two key results emerge from Table 3. 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: 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

3 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.

Table 2: 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

3.1 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 of 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.

Table 3: Case-fatality Rates, COVID-19 (averages May 14-June 14, 2020)

Age Group	Infected	Deceased	Case-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%
≥ 80	4,522	926	20.5%

Source: Computed with data from the Portuguese Health Authority.

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).

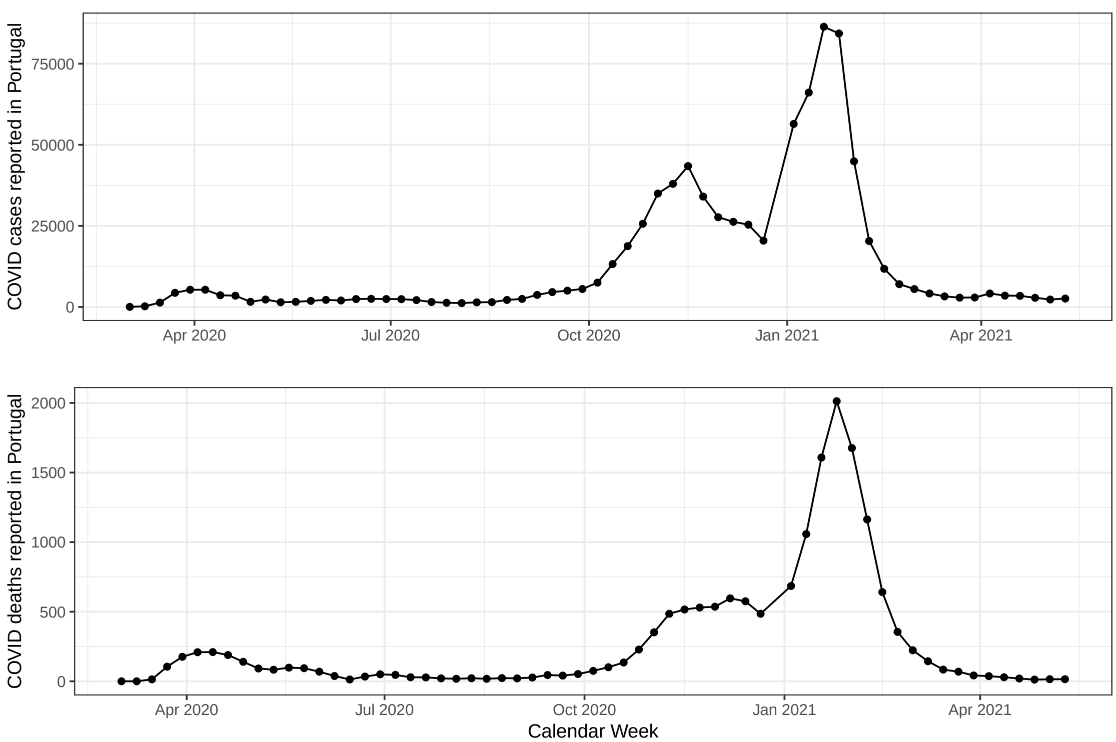

Figure 1: COVID-19 cases and deaths reported by the Portuguese Health Authority (May 20, 2021).

Over the period 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.[6] 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 3 depicts the average logarithm of public servants' monthly consumption expenditures from January 2018 to April 2021. 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. Three features emerge from Figure 3. 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

[6] 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.

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.

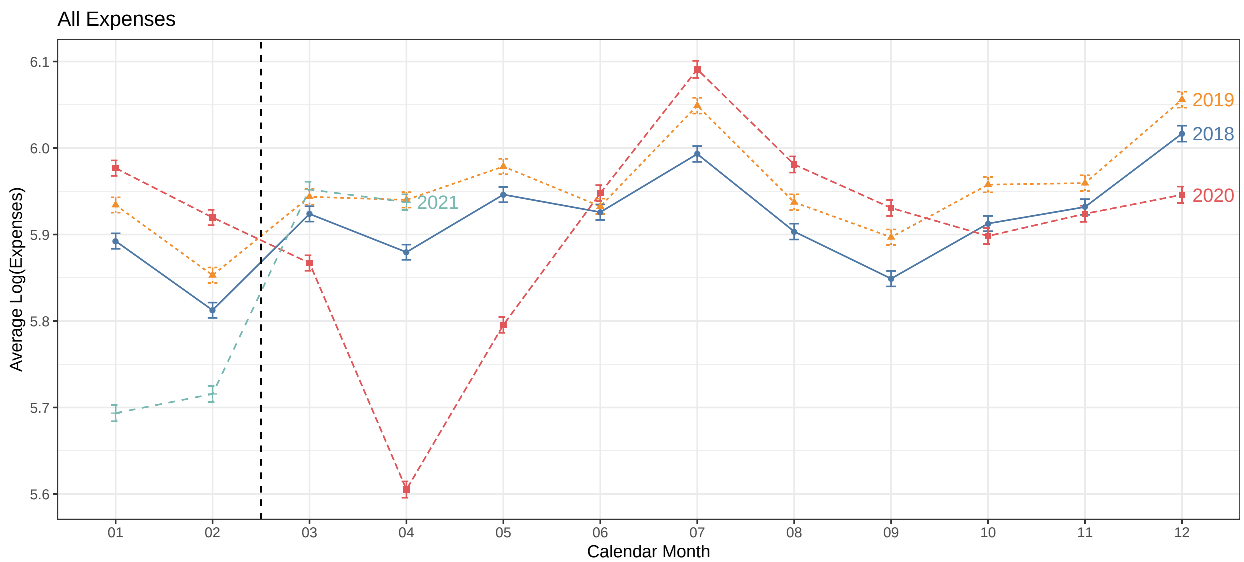

Figure 3: Average of the logarithm of public servants' monthly expenditures.

3.2 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:

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

Subscripts i and t denote person i and calendar month t, respectively. The coefficient Λ 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 λ_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 Δ_d represent the change in spending for people in the reference group (aged 20-49) during epidemic date d. The coefficient δ_{dg} measures the additional change in spending for age group g in epidemic date d.[7] The variable ϵ_{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).[8]

Column 4 of Table 12 reports our parameter estimates. Figure 4 displays our estimates of the impact of Covid on consumption expenditures of different age groups (Δ_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. The non-linear effect of age on consumer expenditures mirrors the non-linear dependency of case-fatality rates on age. On average, over the whole sample, people aged 20-49 and those in their 50s, 60s, and 70s cut their expenditures by 10.3, 10.7, 14.6, and 18.7 percent, respectively. The difference between the expenditures of consumers older than 60 and those younger than 49 is statistically significant at a 5 percent level. The difference between the consumption expenditures of people in their 50s and people younger than 49 is not statistically significant at a 10 percent level in most months (see column 4 of Table 12. Third, the decline in consumption for each age group was similar in the first and third waves. At the peak of the first wave, people aged 20-49 and those in their 50s, 60s, and 70s cut their expenditures by 31.6, 32.6, 39.3, and 45.4 percent, respectively. At the peak of the third wave, people aged 20-49 and those in their 50s, 60s, and 70s cut their expenditures by 29.6, 29.6, 33.7, and 39.8 percent.

One potential reason why the consumption expenditures of old and young people responded differently to Covid is that these groups purchase different goods and services that were differentially affected by lockdowns. To investigate this possibility, we estimate the

[7] We keep age groups constant based on a persons' age in the year 2020.

[8] 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).

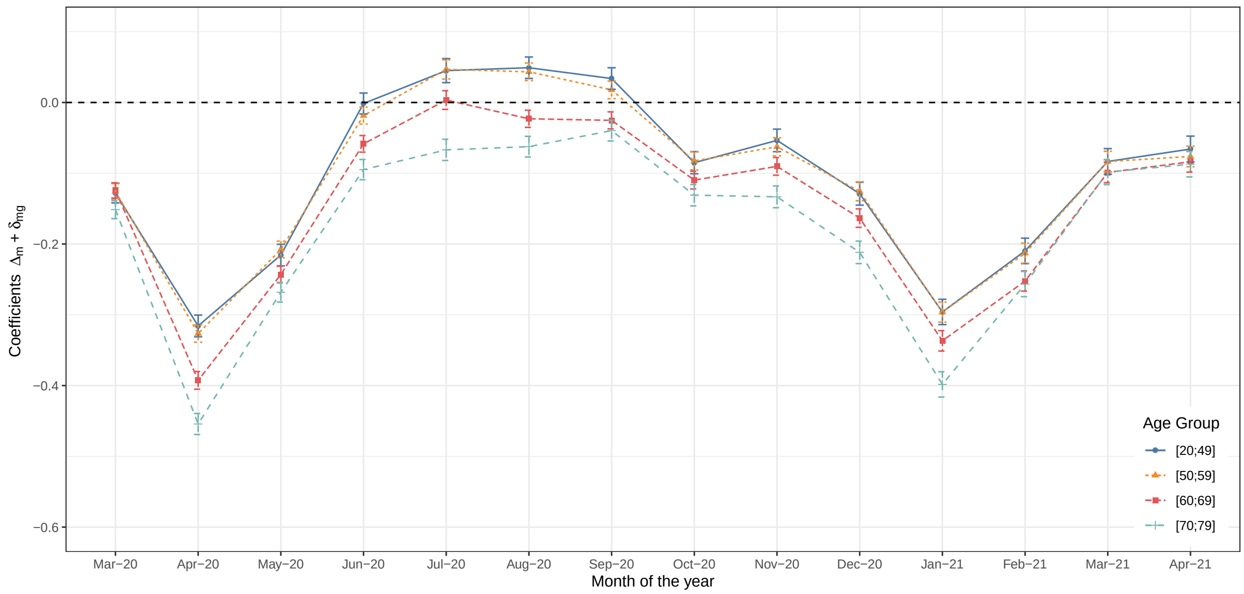

Figure 4: Changes in expenditures of public servants during the epidemic relative to a counterfactual without Covid.

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 the law 78-A/2020 approved on September 29, 2020. Figure 5, which is the analog to Figure 4, presents our results. Two features are worth noting. First, all groups cut their consumption expenditures by about the same in the first and the third waves of the epidemic. Second, the old cut their consumption by more than the young in the epidemic's first, second, and third waves.

3.3 The response of people with different income

The economic model discussed in Section 4 implies that to reduce the risk of infection, high-income people cut their expenditures by more than low-income people. 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 3.2 might conflate the effect of age and income.

Table 13 in the appendix reports our parameter estimates. Figure 6 displays our estimates of the impact of Covid on consumption expenditures of different age groups (Δ_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

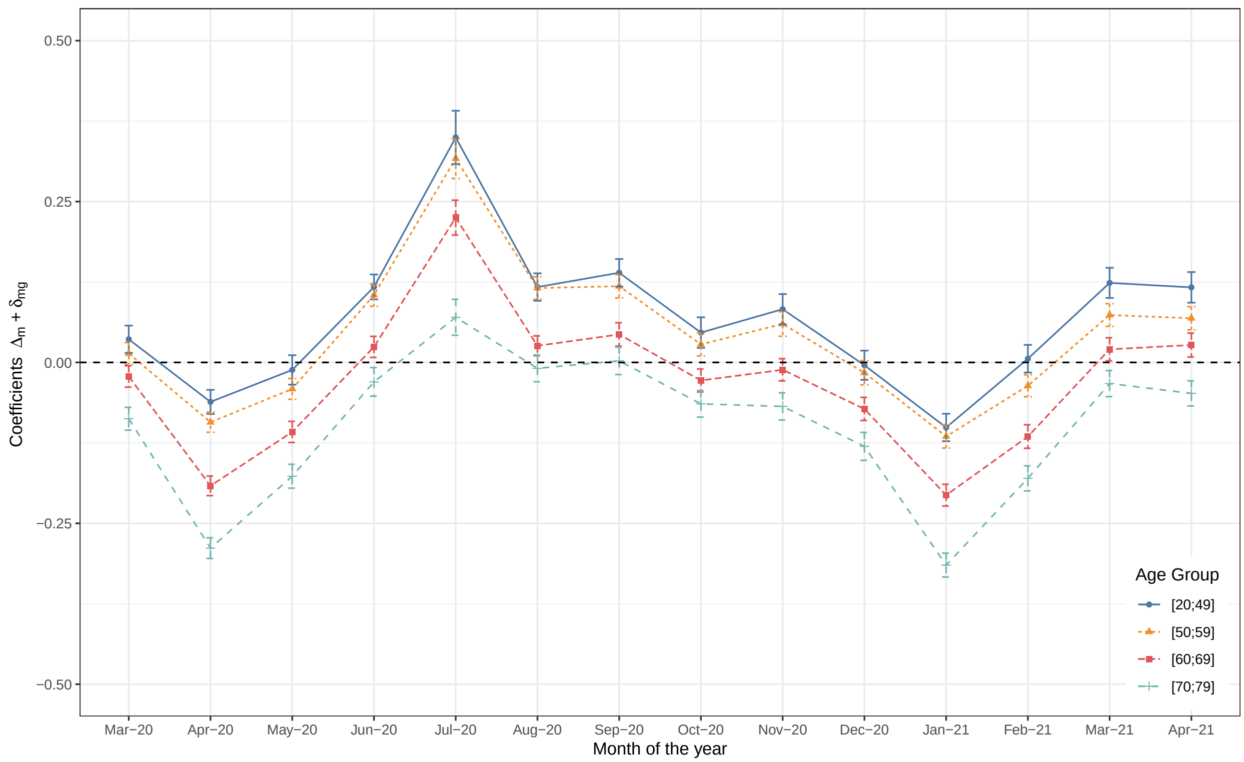

Figure 5: Changes in expenditures of public servants in the sectors least affected by lockdowns during the epidemic relative to a counterfactual without Covid.

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

3.4 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.[9] A natural question is whether people with comorbidities react to that risk by reducing consumption more than people who do not have comorbidities.

[9]See the Center for Disease Control (`https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/evidence-table.html`) for a thorough review of these comorbidities.

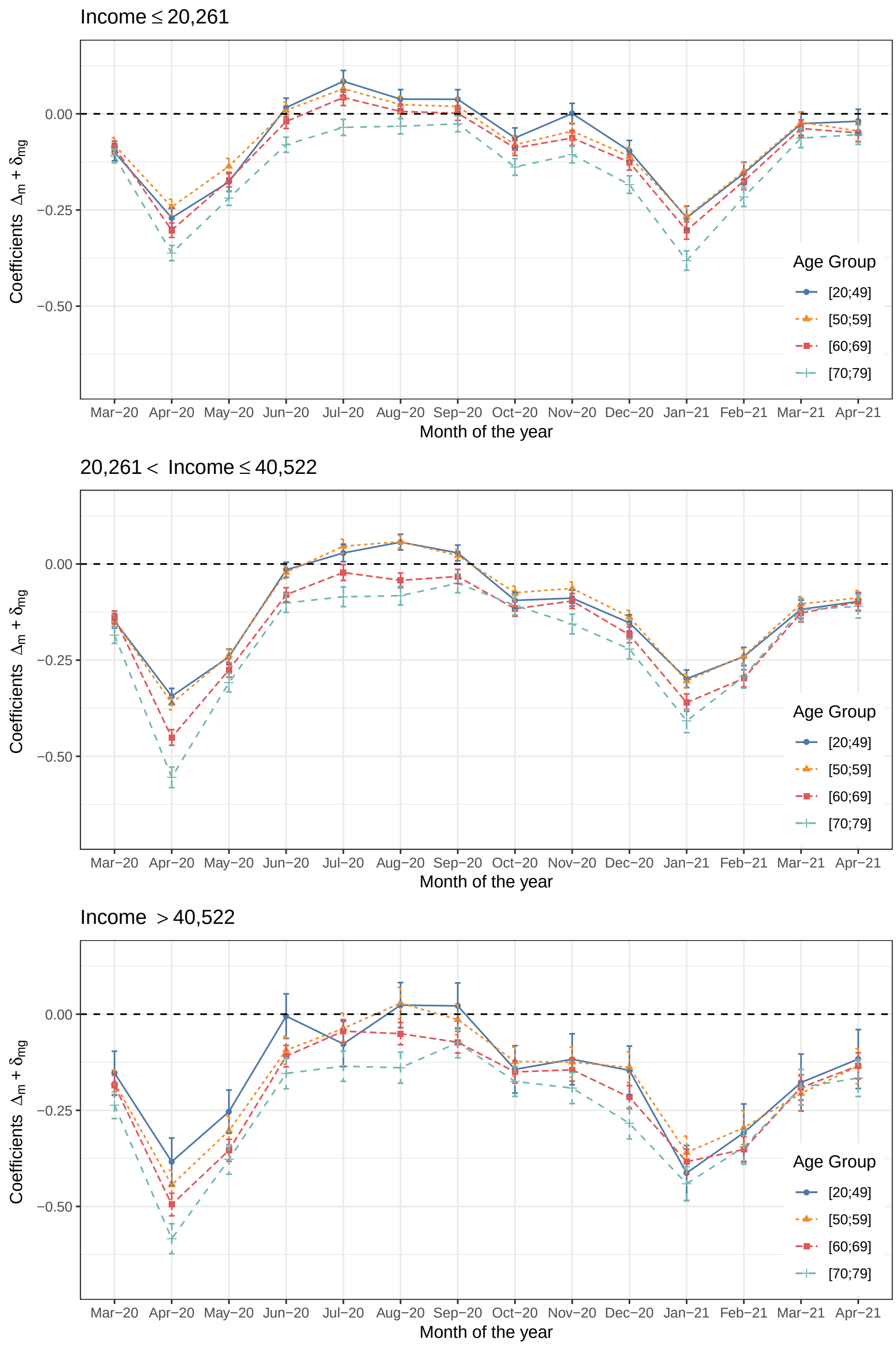

Figure 6: Changes in expenditures of public servants in different income groups during the epidemic relative to a counterfactual without Covid.

We do not have the health history of 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 2021. For this reason, we restrict our sample to the period from January 2018 to December 2020.

Table 14 in the Appendix reports our parameter estimates. The key result is displayed in Figure 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 who have 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 continues to be 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.

3.5 Robustness

In the Appendix, we report the results of four 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 re-do 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 re-do our empirical analysis for retirees instead of public servants. Retirees are another group of people whose income is likely to have remained relatively stable during the epidemic. Our

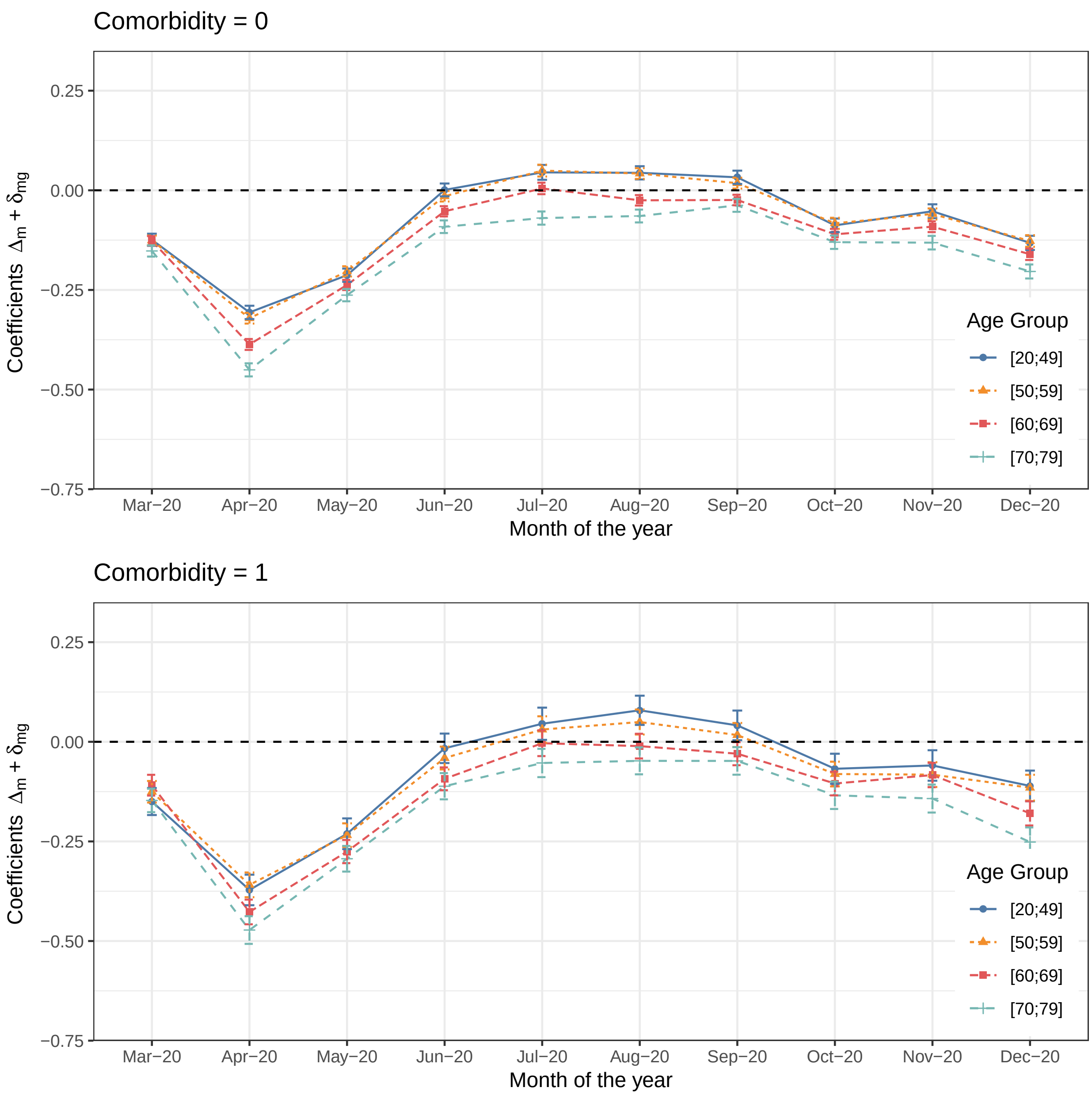

Figure 7: Changes in the expenditures of public servants during the epidemic relative to a counterfactual without Covid for people with and without comorbidity.

results are similar to those that we obtain for public servants.[10] We find that conditioning on age, the consumption expenditures of civil servants and retirees respond similarly to Covid.

[10]The average retiree in the overall population is older than the average civil servant. There is also less age dispersion in the pool of retirees than in the pool of civil servants. See Table 2.

4 A model of risk-taking behavior

In this section, we focus our model-based analysis on two questions. First, what role do people's beliefs about their case-fatality rate play? Second, what fraction of the drop in consumption is due to people's risk-avoidance behavior as opposed to government-imposed containment measures?

To answer these questions, 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.

Throughout, we assume that people know the objective probability of becoming infected. However, they don't know their age group's true 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 hope to 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 that 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, in principle, 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.

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. We refer to these groups as young and old for ease of exposition. 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 there are only two types of people in the model. 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 7 in which we discuss the implications of endemic Covid.

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

$$b_{a,t+1} = w + (1+r)b_{a,t} - c_{a,t},$$

where w is the real wage rate and $b_{a,t}$ is the amount invested in an asset that yields a real interest rate r.

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

$$\tau_{a,t} = \pi_1 c^h_{a,t} I_t + \pi_2 I_t, \tag{2}$$

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 et al. (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 their case-fatality rate. At the beginning of the epidemic, people of age a believe that the case-fatality rate is $\pi_{ad,0}$. They update these beliefs using a parsimonious constant-gain learning algorithm.[11]

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

Here, π^*_{da} is the true case-fatality rate for people of age a. The parameters $g_a \in [0,1]$ control how quickly people update their beliefs.[12] These beliefs converge in the long run to π^*_{da}. Implicitly, this specification assumes that, in every period, people see the 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:

$$E_t\left(\pi_{ad,t+j}\right) = \pi_{ad,t}.$$

The variable δ_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 $\pi_{ar,t}$. Consistent with this assumption, people's expectation of the amount of time it takes to resolve a Covid infection is constant over time.

We assume that people's utility has the recursive form proposed by Kreps and Porteus (1978), Weil (1989), and Epstein and Zin (1991). A virtue of this specification is that it separates the coefficient of relative risk aversion from the elasticity of intertemporal substitution. The lifetime utility of a person with age a and health status h at time t is

$$U^h_{a,t} = z + \left[(1-\beta_t)(c^h_{a,t})^{1-\rho} + \beta_t\left\{E_t\left[\left(U^h_{a,t+1}\right)\right]^{1-\alpha}\right\}^{(1-\rho)/(1-\alpha)}\right]^{1/(1-\rho)}.$$

Here, z is a constant that influences the value of life (see Hall and Jones (2007)), β_t is the discount factor, α is the coefficient of relative risk aversion for static gambles, and ρ is the inverse of the intertemporal elasticity of substitution with respect to deterministic income changes. The case of $\rho = \alpha$ corresponds to time-separable expected discounted utility. 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, $\{I_t\}_0^\infty$.

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

[12] 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 more complex information structures.

We use time variation in β_t to model exogenous changes in consumption demand associated with government-imposed containment measures:

$$(1-\beta_t) = (1-\beta)(1-\mu_t). \tag{3}$$

Here, β denotes the household's discount rate and μ_t represents the consumption wedge introduced by containment measures. Equation (3) implies that the higher is μ, i.e., the more containment there is, the lower is the marginal utility of consumption.

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 β_t, I_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.[13]

The value function of a young susceptible person at time t is

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

Recall that v is the probability of a young person becoming old. U^i_{yt} and U^i_{ot} 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 δ_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:

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

where $\omega_0 > 0$ and $\omega_1 > 0$. The bequest motive allows the model to be consistent with three empirical observations. First, many people die with large asset holdings (see e.g. Huggett (1996) and De Nardi and Yang (2014)). Second, the consumption expenditures of older

[13] To simplify the notation, we do not explicitly index value functions by a person's current belief about case-fatality rates.

people are lower than those of younger people. The latter pattern obtains in the model because, as people get older, bequests receive a higher weight in the utility function relative to consumption. Third, bequests are a superior good. The latter observation is consistent with the model when $\omega_0 > 0$.

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

$$\begin{aligned} U^s_{o,t}(b_t) &= z + \{(1-\beta_t)(c^s_{o,t})^{1-\rho} + \beta_t[(1-\tau_{o,t})(1-\delta_o)\left(U^s_{o,t+1}(b_{t+1})\right)^{1-\alpha} \\ &\quad +\tau_{o,t}(1-\delta_o)\left(U^i_{o,t+1}(b_{t+1})\right)^{1-\alpha} + \delta_o B(b_{t+1})^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)}. \end{aligned}$$

With probability δ_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, $U^i_{y,t}(b_t)$, is

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

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

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

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

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

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

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

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 δ_y.

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

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

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

5 Model parameters

We partition the model's parameters into two sets. The first set is estimated with Bayesian methods discussed in Christiano et al. (2010), Christiano et al. (2016), and Fernández-Villaverde et al. (2016). The second set is calibrated to micro data.

5.1 Econometric methodology

We estimate younger and older people's initial prior beliefs about case-fatality rates (π_{yd0} and π_{od0}), the gain parameters (g_y and g_o), and the parameter μ. This parameter controls the impact of containment on the marginal utility of consumption. We assume that the containment wedge μ_t defined in equation (2) is given by

$$\mu_t = \mu\xi_t,$$

where μ is a scalar and ξ_t is the time series for containment measures depicted in Figure 2. The maximum value of ξ_t is normalized to one.

Let the vector ψ 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 ψ for these two groups of people obtained using regression 1. Appendix A.3 reports the estimated regression parameters. 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:

$$\hat{\psi}_t = \sum_{m=Mar,2020}^{Apr,2021} \hat{\Delta}_m After_t \times \mathbf{1}\{Month_t = m\} + \sum_{m=Mar,2020}^{Apr,2021} \hat{\delta}_{mg} After_t \times \mathbf{1}\{Month_t = m\} \times \mathbf{1}\{AgeGroup_i = old\}. \tag{4}$$

The dashed blue and red lines of Figure 8 display the values of $\hat{\psi}$ for young and old people. The bars around point estimates represent 95 percent confidence intervals.

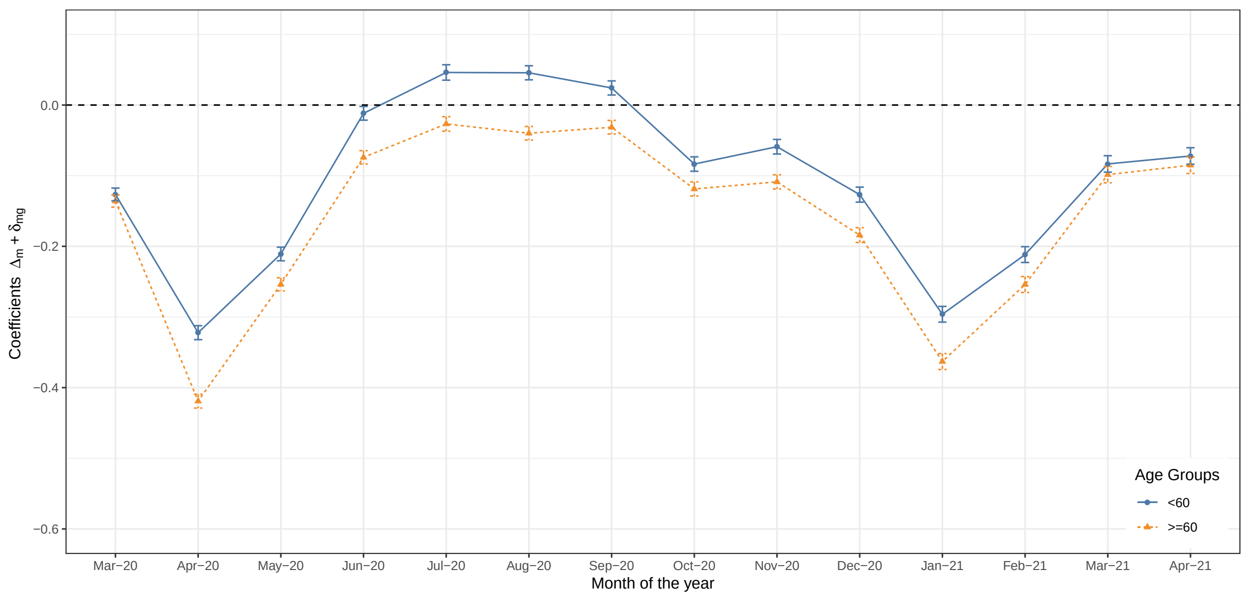

Figure 8: Changes in the expenditures of public servants during the epidemic relative to a counterfactual without Covid for people younger and older than 60.

Our estimation criterion focuses on the consumption response of people who have a net wealth of 75 thousand euros. According to the Survey of Household Financial Conditions Statistics-Portugal (2017); 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 in every iteration of the estimation algorithm the consumption behavior of people with different wealth levels.[14]

[14]It takes about 1.5 seconds to simulate the model on a 2.3 GHz Quad-Core Intel Core i7 CPU machine

The logic of the estimation procedure is as follows. Suppose that our structural model is true. Denote the true values of the model parameters by θ_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

$$\hat{\psi} \overset{a}{\sim} N(\psi(\theta_0), V). \tag{5}$$

Here, V is a consistent estimate of the precision matrix $W(\theta_0)/T$. Following Christiano et al. (2010), Christiano et al. (2016), and Fernández-Villaverde et al. (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 10.

In our analysis, we treat $\hat{\psi}$ as observed data. We specify priors for θ and then compute the posterior distribution for θ given $\hat{\psi}$ using Bayes' rule. This computation requires the likelihood of $\hat{\psi}$ given θ. Our asymptotically valid approximation of this likelihood is motivated by (5):

$$f\left(\hat{\psi}|\theta, V\right) = (2\pi)^{-\frac{N}{2}} |V|^{-\frac{1}{2}} \exp\left[-0.5\left(\hat{\psi} - \psi(\theta)\right)' V^{-1}\left(\hat{\psi} - \psi(\theta)\right)\right]. \tag{6}$$

The value of θ that maximizes this function is an approximate maximum likelihood estimator of θ. It is approximate for two reasons. First, the central limit theorem underlying (5) 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 θ conditional on $\hat{\psi}$ and V is:

$$f\left(\theta|\hat{\psi}, V\right) = \frac{f\left(\hat{\psi}|\theta, V\right) p(\theta)}{f\left(\hat{\psi}|V\right)}. \tag{7}$$

with 32 gigabytes of RAM for a given wealth level. With the full state space (150 grid points for assets) it takes roughly 4 minutes to simulate the model. We use a standard MCMC algorithm to compute the mode and posterior distribution of the parameters using 100.000 draws (11 chains, 10 percent of draws used for burn-in, draw acceptance rates around 0.2).

Here, $p(\theta)$ denotes the prior distribution of θ 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 θ, we can compute the mode of the posterior distribution of θ by maximizing the value of the numerator in (7). 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 implication for the marginal likelihood of $\hat{\psi}$ computed using the Laplace approximation.

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

5.1.1 Calibration

The set of parameters that we calibrate is given by: π_1, π_2, π_{dy}, π_{do}, r, α, ρ, β, δ_y, δ_o, z, ω_0, and ω_1. We begin by discussing the calibration procedure for π_1 and π_2. It is common in epidemiology to assume that the relative importance of different modes of transmission is similar across viruses that cause respiratory diseases. Ferguson et al. (2006) argue that, in the case of influenza, 30 percent of transmissions occur in the household, 33 percent in the general community, and 37 percent in schools and workplaces. To map these estimates into our transmission parameters, we proceed as follows. We use the Statistics Portugal 1999 Survey of Time Use to estimate the percentage of time spent on general community activities devoted to consumption. We compute the latter as the fraction of time spent purchasing goods and services or eating and drinking outside the home. To estimate the time spent eating and drinking outside the home, we multiply the time spent eating and drinking by the fraction of total food expenditures on food away from home in 2019. We estimate this fraction as the ratio of expenditures in restaurants and hotels to the sum of expenditures in restaurants and hotels and on food, drink and tobacco (42 percent). These considerations imply that the fraction of time spent on general community activities related to consumption is 48 percent. Since 33 percent of transmissions occur in the general community, we estimate that roughly one-sixth of transmissions are related to consumption (0.33×0.48, which is approximately one-sixth).

The parameter π_1 is set so that one-sixth of initial infections are due to consumption-related interactions. We set the parameter π_2 so that the basic reproduction number, $\mathcal{R}_0$, is

2.5 when consumption equals its steady state value. This value of $\mathcal{R}_0$ is the one preferred by the Center for Disease Control.[15]

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 $\delta_o = 1/(13 \times 52)$ and $\delta_y = 1/(51 \times 52)$. Since the average age difference between old and young people is 28 years, we set the weekly probability of aging, ν, 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 actual weekly case-fatality rates π_{dy} and π_{do} 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 3).

We set the coefficient of relative risk aversion (α) to 2 and the intertemporal elasticity of substitution ($1/\rho$) 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 towards risk. The weekly discount factor, β, 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 (ω_0 and ω_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 $\omega_0 = 120$, $\omega_1 = 4$, and $z = 2$.

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.

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

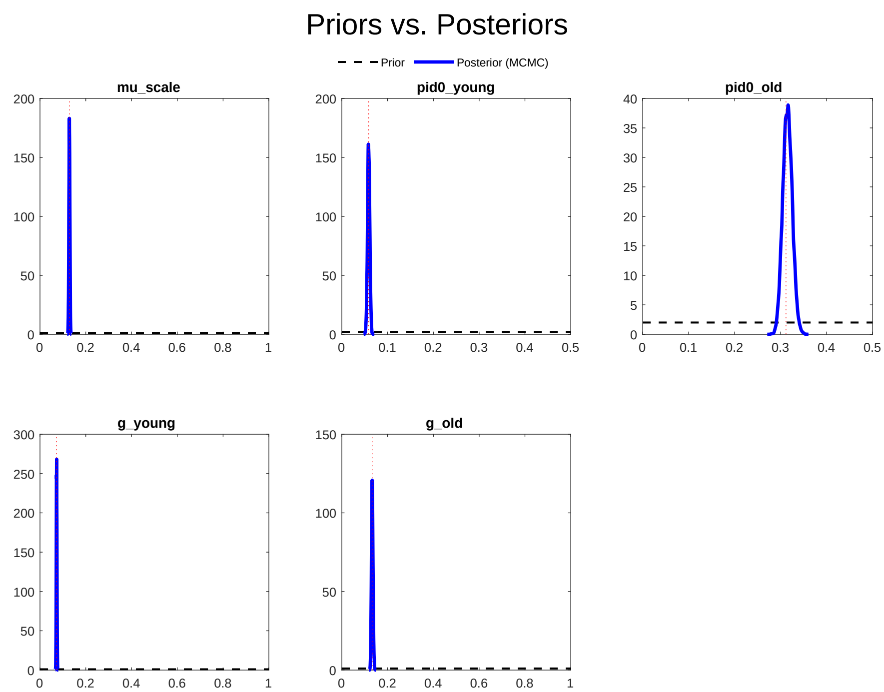

Figure 9: Priors and posteriors of estimated parameters.

6 Empirical results

Figure 9 shows the priors and the posteriors for the parameters we estimate. This figure shows that the data is very informative relative to our priors. Table 4 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 π_{dy0} and π_{do0} are 0.059 and 0.312, respectively. Recall that case-fatality rates for young and old are $\pi_{dy} = 7 \times 0.001/14 = 0.0005$ and $\pi_{do} = 7 \times 0.035/14 = 0.0175$, respectively. So, according to the model, both younger and older people greatly overestimated their case-fatality rates at the beginning of the epidemic.

Second, the posterior mode of the gain parameters, g_y and g_o, are 0.073 and 0.133, respectively. Figure 10 displays the implied time series of π_{dyt} and π_{dot}. By the end of the sample, π_{dyt} and π_{dot} 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 μ is equal to 0.129. So, at their peak, containment measures reduced the marginal utility of consumption by roughly 13 percent.

Table 4: Priors and Posteriors of Parameters: Baseline Model vs. No-Learning Model

		Baseline Model	No Learning Model
	Prior Distribution	Posterior Distribution	Posterior Distribution
	D,Mean,[2.5-97.5%]	Mode, [2.5-97.5%]	Mode, [2.5-97.5%]
Initial belief, mortality rate of the young,π_{0dy}	U, 0.25, [0.013 0.488]	0.059, [0.054 0.064]	
Initial belief, mortality rate of the old,π_{0do}	U, 0.25, [0.013 0.488]	0.312, [0.296 0.336]	
Learning speed parameter of the young, g_y	U, 0.50, [0.025 0.975]	0.073, [0.070 0.076]	
Learning speed parameter of the old,g_o	U, 0.50, [0.025 0.975]	0.133, [0.126 0.140]	
Containment parameter μ	U, 0.50, [0.025 0.975]	0.129, [0.124 0.133]	0.205, [0.202 0.208]
Log Marginal Likelihood (Laplace)		-495.3	-1777.1

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 100,000 draws (11 chains, 10 percent of draws used for burn-in, draw acceptance rates about 0.2).U denotes uniform distribution.

The dashed red and blue lines in Figure 11 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.

Figure 11 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

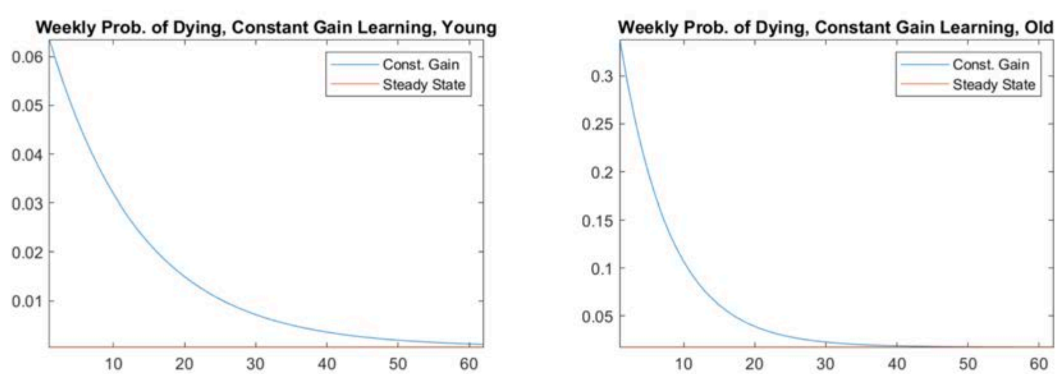

Figure 10: Evolution over time of beliefs about case-fatality rates of old and young.

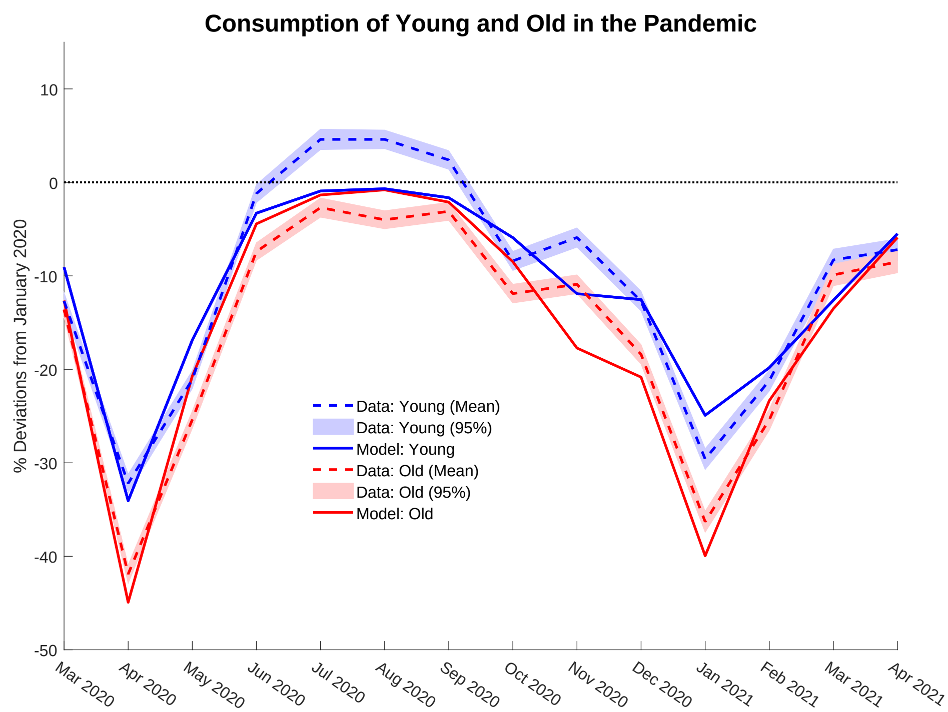

Figure 11: Baseline model and data implications for changes in the expenditures of public servants during the epidemic relative to a counterfactual without Covid.

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 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.

6.1 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 consumption of older and younger people is similar in the first and third wave. But the risk of becoming infected is much larger in the third wave. A model in which people know their true case-fatality rate at the beginning of the epidemic cannot account for this feature of the data.

To formally substantiate this claim, we estimate a version of the model in which people know the true case-fatality rates at the beginning of the epidemic. This assumption is standard in the Covid literature (e.g., Alvarez et al. (2021), Eichenbaum et al. (2021), and Jones et al. (2021)).

In this version of the model, the only estimated parameter is μ. The last column of Table 4 reports the mean and 95 percent probability intervals for the prior and posterior of μ. Interestingly, the posterior mode of μ is higher than the corresponding value in the benchmark model. This higher value improves the model's fit during the first wave but does not help the model explain the differential response of the old and the young.

We evaluate the performance of this model relative to the learning model by computing its implications for the marginal likelihood. The marginal log likelihood of the no-learning model is a dramatic $1,282$ points lower than that of the learning model. To understand this result, consider Figure 12, which displays the implications of the re-estimated model with no learning for the consumption expenditures of younger and older people.

First, the model substantially understates the drop in the consumption expenditures of old people during the first wave of the epidemic. Second, for the period up to November

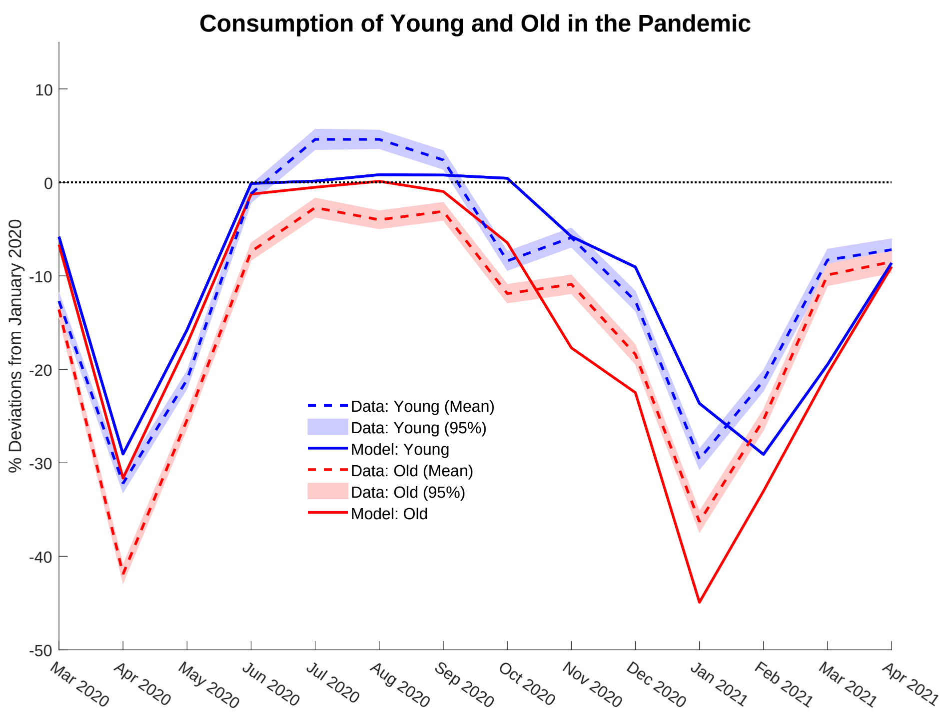

Figure 12: Model with no learning and data implications for changes in the expenditures of public servants during the epidemic relative to a counterfactual without Covid.

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, 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.

6.2 The impact of containment

A natural way to understand the impact of containment measures on consumption expenditures would be to solve the model setting containment rates to zero. But, to do so, one would have to construct the counterfactual path for aggregate infections that would obtain in the absence of containment. Doing so would require a general equilibrium model that would embed a host of additional assumptions. Instead, we compute the counterfactual fall in expenditures that would have taken place 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 13 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 13 shows that the containment measures in isolation would have led to an 18 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 decline in consumption for both groups reflects their response to the risk of dying from Covid. These results are consistent with the findings of Chetty et al. (2020), Goolsbee and Syverson (2020), and Villas-Boas et al. (2020).

7 The economic impact of endemic Covid

This section investigates the economic costs of endemic Covid in an economy where people know the actual case-fatality rates. Doing so requires changing our model in three ways. First, we modify our epidemiology model so that Covid becomes endemic. Second, we

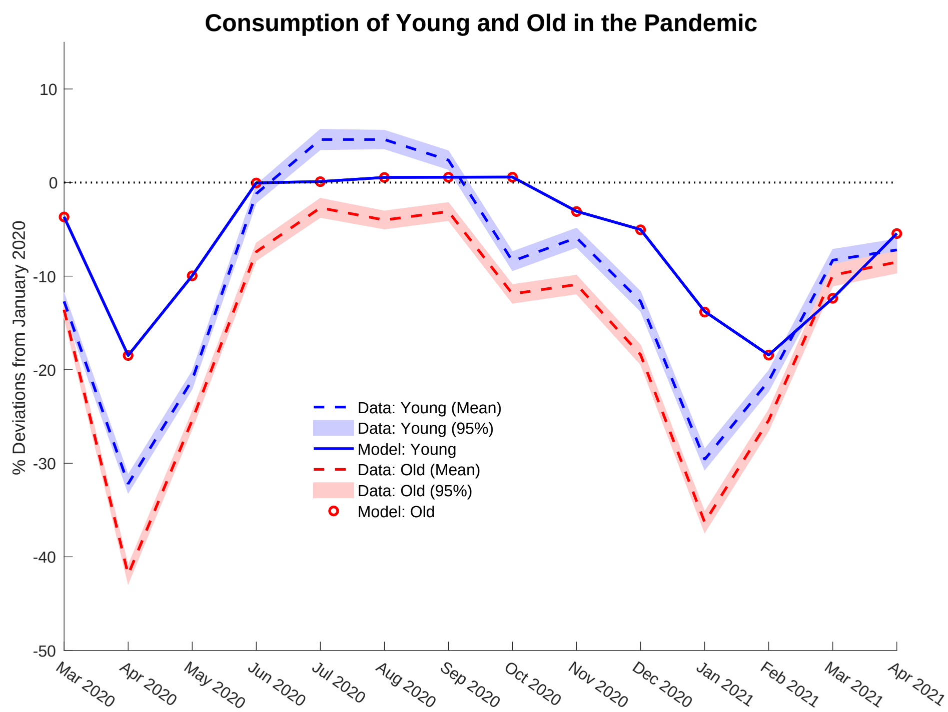

Figure 13: Model with only containment and data implications for changes in the expenditures of public servants during the epidemic relative to a counterfactual without Covid.

allow for vaccination. Third, we embed that model in a general equilibrium framework with endogenous labor choice and capital accumulation.

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 true 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 π_{dy0} and π_{do0} and do not update them.

7.1 Endemic Covid

As in Eichenbaum et al. (2022b) and Abel and Panageas (2020), we modify social dynamics so that recovered people become susceptible with probability π_s. This modification implies that the pool of sustainable 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.

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

$$\begin{aligned} T_{a,t} &= \pi_1 S_{a,t}(1-\phi_a)C^s_{a,t}(I_{y,t}C^i_{y,t} + I_{o,t}C^i_{o,t}) + \pi_2 S_{a,t}(1-\phi_a)N^s_{a,t}(I_{y,t}N^I_{y,t} + I_{o,t}N^I_{o,t}) \quad (8) \\ &+\pi_3 S_{a,t}(1-\phi_a)\left(I_{y,t} + I_{o,t}\right). \end{aligned}$$

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 total hours worked of susceptible and infected people of age a, respectively.

Susceptible younger and older people are vaccinated with probability ϕ_y and ϕ_o, respectively. 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 π_1 reflects both the amount of time spent in consumption activities and the probability of becoming infected as a result of 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 π_2 reflects the probability of becoming infected as a result of 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 number of young and old susceptible people at time $t+1$ is given by:

$$S_{y,t+1}=[S_{y,t}(1-\phi_y)-T_{y,t}](1-\delta_y-\upsilon)+\pi_s R_{y,t}+\mathfrak{B}_{y,t}, \tag{9}$$

$$S_{o,t+1}=[S_{o,t}(1-\phi_o)-T_{o,t}](1-\delta_o)+[S_{y,t}(1-\phi_y)-T_{y,t}]\upsilon+\pi_s R_{o,t}+\mathfrak{B}_{o,t}. \tag{10}$$

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

$$I_{y,t+1}=I_{y,t}(1-\pi_{yr}-\pi_{yd})(1-\delta_y-\upsilon)+T_{y,t}(1-\delta_y-\upsilon), \tag{11}$$

$$I_{o,t+1}=I_{o,t}(1-\pi_{or}-\pi_{od})(1-\delta_o)+T_{y,t}\upsilon+T_{o,t}(1-\delta_o)+I_{y,t}(1-\pi_{yr}-\pi_{yd})\upsilon. \tag{12}$$

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

$$R_{y,t+1}=R_{y,t}(1-\delta_y-\upsilon-\pi_s)+\phi_y S_{y,t}(1-\delta_y-\upsilon)+I_{y,t}\pi_{yr}(1-\delta_y-\upsilon), \tag{13}$$

$$R_{o,t+1}=R_{o,t}(1-\delta_o-\pi_s)+\phi_o S_{o,t}(1-\delta_o)+\upsilon\phi_y S_{y,t}+R_{y,t}\upsilon+I_{y,t}\pi_{yr}\upsilon+I_{o,t}\pi_{or}(1-\delta_o). \tag{14}$$

7.2 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. So, 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 4 to allow for endogenous labor supply. The household's lifetime utility is given by

$$U_t = z + m_t + \beta \left(E_t U_{t+1}^{1-\alpha} \right)^{1/(1-\alpha)} = z + m_t + \beta U_{t+1}, \tag{15}$$

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 of people with age a and health status h, respectively. The utility function of a person with age a and health status h is

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

The household budget constraint is given by

$$\sum_{a \in \{o,y\}} (s_{a,t} c^s_{a,t} + i_{a,t} c^i_{a,t} + r_{a,t} c^r_{a,t}) + k_{t+1} - (1-\delta_k) k_t = w_t \sum_{a \in \{o,y\}} (s_{a,t} n^s_{a,t} + i_{a,t} n^i_{a,t} + r_{a,t} n^r_{a,t}) + R^k_t k_t. \tag{16}$$

Here, k_t denotes the stock of capital, δ_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:

$$\begin{aligned} \tau_{a,t} &= \pi_1 s_{a,t} (1-\phi_a) c^s_{a,t} (I_{y,t} C^I_{y,t} + I_{o,t} C^I_{o,t}) + \pi_2 s_{a,t} (1-\phi_a) n^s_{a,t} (I_{y,t} N^I_{y,t} + I_{o,t} N^I_{o,t}) \\ &\quad + \pi_3 s_{a,t} (1-\phi_a) \left(I_{y,t} + I_{o,t} \right). \end{aligned} \tag{17}$$

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 ϕ_o of old susceptibles and a fraction ϕ_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:

$$s_{y,t+1} = [s_{y,t}(1-\phi_y) - \tau_{y,t}](1-\delta_y - \upsilon) + \pi_s r_{y,t} + \mathfrak{b}_{y,t}, \tag{18}$$

$$s_{o,t+1} = [s_{o,t}(1-\phi_o) - \tau_{o,t}](1-\delta_o) + [s_{y,t}(1-\phi_y) - \tau_{y,t}]\upsilon + \pi_s r_{o,t} + \mathfrak{b}_{o,t}, \tag{19}$$

$$i_{y,t+1} = i_{y,t}(1-\pi_{yr} - \pi_{yd})(1-\delta_y - \upsilon) + \tau_{y,t}(1-\delta_y - \upsilon), \tag{20}$$

$$i_{o,t+1} = i_{o,t}(1-\pi_{or} - \pi_{od})(1-\delta_o) + \tau_{y,t}\upsilon + \tau_{o,t}(1-\delta_o) + i_{y,t}(1-\pi_{yr} - \pi_{yd})\upsilon, \tag{21}$$

$$r_{y,t+1} = r_{y,t}(1-\delta_y - \upsilon - \pi_s) + \phi_y s_{y,t}(1-\delta_y - \upsilon) + i_{y,t}\pi_{yr}(1-\delta_y - \upsilon), \tag{22}$$

$$r_{o,t+1} = r_{o,t}(1-\delta_o - \pi_s) + s_{o,t}\phi_o(1-\delta_o) + \upsilon\phi_y s_{y,t} + r_{y,t}\upsilon + i_{y,t}\pi_{yr}\upsilon + i_{o,t}\pi_{or}(1-\delta_o). \tag{23}$$

The household maximizes (15) subject to the budget constraint (16) and to the laws of motion for the health status of family members (equations (17)-(23)). The first-order conditions for the consumption of people with age a are

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

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

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

The first-order conditions for hours worked of people with age a are

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

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

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

The first-order condition for k_{t+1} is

$$\lambda^b_t = \beta\lambda^b_{t+1}(R^k_{t+1} + 1 - \delta_k).$$

It is useful to define the following derivatives

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

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

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

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

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

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

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

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

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

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

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

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

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

7.3 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:

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

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

7.4 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,

$$\begin{aligned}
C_t &= \sum_{a\in\{o,y\}} \left[S_{a,t}C_{a,t}^s + I_{a,t}C_{a,t}^i + R_{a,t}C_{a,t}^r\right], \\
N_t &= \sum_{a\in\{o,y\}} \left[S_{a,t}N_{a,t}^s + I_{a,t}N_{a,t}^i + R_{a,t}N_{a,t}^r\right], \\
C_t + K_{t+1} &= AK_t^{1-\gamma}N_t^{\gamma} + (1-\delta_k)K_t.
\end{aligned}$$

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 law of motion for the aggregate capital stock is:

$$K_{t+1} = X_t + (1-\delta)K_t.$$

The market for physical capital clears

$$K_t = k_t.$$

7.5 Steady-state properties

This section discusses the calibration of the model and the steady-state implications of endemic Covid. The system of equations that defines the steady state is detailed in the Technical Appendix available on the authors' websites.

7.5.1 Calibration

With one exception, parameters common to the partial- and general-equilibrium model are set to the values discussed in Section 5. 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 dollars.

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 part of income received by self-employed workers attributable to labor. The weekly rate of capital depreciation δ_k is $0.1/52$.

In Section 5, we argue that roughly one-sixth of transmissions are related to consumption. Here we use a similar procedure to estimate the fraction of infections that occur in the workplace. Recall that Ferguson et al. (2006) argues that 37 percent of transmissions arise in schools and workplaces. To compute the fraction of transmissions that occur in the workplace, we weigh the number of students by ten and the number of workers by four. These weights are the average number of contacts per day at school and work reported by Lee et al. (2010). According to Statistics Portugal, the number of students and workers in 2019 is 1.9 million and 5.2 million, respectively. These considerations imply that the fraction of transmissions occurring in the workplace is 52 percent (5.2 x 4/(5.2 x 4 + 1.9 x 10)). Since 37 percent of transmissions arise in schools and workplaces, 18 percent (0.37 x 0.52) of transmissions, or roughly one-sixth, are related to work. Accordingly, we set π_1 and π_2 so that 1/6 of infections in the pre-epidemic steady state are due to consumption- and work-related activities, respectively. We set π_3 so that the basic reproduction rate, $\mathcal{R}_0$, is 2.5. Recall that the value of $\mathcal{R}_0$ is the one preferred by the Center for Disease Control. The resulting parameter values are $\pi_1 = 0.0000028153$, $\pi_2 = 0.00026573$ and $\pi_3 = 0.8333$. We choose $\pi_s = 1/26$, which is consistent with the notion that immunity lasts on average for six months.

We set $\phi_y = \phi_o = 1/26$ which implies that roughly 4 percent of the population gets vaccinated each week. This value is roughly 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 pre-epidemic share of old people in the population is 0.3.

According to the Statistics Portugal 1999 Survey of Time Use, people who are employed spend roughly 7 hours per day at work. The fraction of the population employed in 2019 is 57.6 percent. So, average hours worked per week in the population is 28 ($7 \times 7 \times 0.576$). We set $\theta = 0.007401$ so that people work 28 hours per week in the pre-epidemic steady state. We set $A = 1.086265$ so that, as in Section 5, annual income is $19,000$ Euros in the pre-epidemic steady state.

In order 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: $\mathfrak{B}_{y,t} = 0.000712$ and $\mathfrak{B}_{o,t} = 0.000063$. 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. Fifty seven percent of the population is recovered, 42 percent susceptible, and one percent is infected. The fraction of people that die from all causes is 0.08 of 1 percent. Covid accounts for 8.7 percent of these deaths. A fraction 0.35 of 1 percent of the population dies from Covid each year. Average life expectancy at birth falls on a log-percentage basis by 3.2 percent, from 76.2 to 73.8 years.

Table 5: Steady-state effect of endemic Covid

	Case-fatality	
	Posteriors	Priors
Aggregate output	-1.08	-11.80
Aggregate consumption	-1.08	-11.80
Aggregate hours worked	-1.08	-11.80
Consumption young	-0.05	-9.40
Consumption old	-3.50	-17.20
Hours worked young	-0.25	-8.60
Hours worked old	-3.02	-19.00

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 1 percent relative to the pre-epidemic steady state.

Consumption falls by 3.5 percent for old people and barely falls for young people. Hours worked fall by 3 percent for older people and only 0.25 percent for younger people.

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).

It is interesting to compare the impact of endemic covid in our model with Acemoglu and Johnson (2007)'s estimates of the effect of declines in mortality on real GDP. According to their baseline estimates, a one percent increase in life expectancy raises real GDP by 85 basis points (with a standard error of 28 basis points). The corresponding effect in our model is 35 basis points (Covid reduces life expectancy at birth by 3.2 percent and reduces aggregate output by 1.1 percent relative to the pre-epidemic steady state). Taking sampling uncertainty into account, this effect is consistent with Acemoglu and Johnson (2007)'s estimates.

The steady-state economic impact of endemic Covid is very small compared to the massive decline in economic activity experienced in 2020. Interpreted through the lens of our model, this difference 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 prior's about case-fatality rates were much higher than objective 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 prior beliefs. The objective case-fatality rates drive actual population dynamics. Technically, in the first-order conditions for $i_{a,t+1}$, the values of π_{ad} and π_{ar} are set to the estimated initial beliefs in Section 5.

The second column of Table 5 compares consumption and hours worked in this steady state and in 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 about 12 percent. Consumption falls by 17.2 percent for old people and 9.4 percent for young people. Hours worked fall by 19 percent for older people and only 8.6 percent for younger people.

Taken together, our results reconcile 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.

8 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 posteriors 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 would 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 infections diseases.

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A Appendix

This appendix is organized as follows. The first 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 second subsection provides results estimated by age cohort and results obtained using data for retirees instead of public servants. The third 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 Seasonality effects

Equation 1 assumes that, in the absence of the epidemic, the seasonal effects for the January through April 2021 (λ_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 using data from January 2018 through December 2019:

$$\begin{aligned} Log(Expense_{it}) = {} & \Lambda_{2019}\mathbf{1}\{Year_t = 2019\} + \\ & \sum_{m=Feb}^{Dec} \lambda_m \mathbf{1}\{Month_t = m\} + \\ & \sum_{m=Feb}^{Dec} \phi_m \mathbf{1}\{Month_t = m\} \times \mathbf{1}\{Year_t = 2019\} + \boldsymbol{\theta_i} + \epsilon_{it} \end{aligned} \tag{24}$$

The ϕ_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 ϕ_m coefficients should be zero. Table 6 presents the regression coefficients.

Figure 14 displays our estimates of ϕ_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 ϕ_m are small, especially when compared to the changes in consumption expenditures that occur after the Covid shock.

Table 6: 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 (λ_{Feb})	-0.080^{***}	-0.078^{***}	-0.074^{***}	-0.095^{***}	-0.068^{***}
	(0.004)	(0.008)	(0.007)	(0.007)	(0.008)
Mar (λ_{Mar})	0.031^{***}	0.022^{**}	0.037^{***}	0.018^{**}	0.049^{***}
	(0.004)	(0.008)	(0.007)	(0.006)	(0.008)
Apr (λ_{Apr})	-0.013^{***}	-0.005	-0.003	-0.026^{***}	-0.013
	(0.004)	(0.009)	(0.007)	(0.007)	(0.008)
May (λ_{May})	0.054^{***}	0.061^{***}	0.061^{***}	0.040^{***}	0.058^{***}
	(0.004)	(0.009)	(0.007)	(0.007)	(0.008)
Jun (λ_{Jun})	0.033^{***}	0.043^{***}	0.043^{***}	0.026^{***}	0.026^{**}
	(0.004)	(0.009)	(0.007)	(0.007)	(0.009)
Jul (λ_{Jul})	0.101^{***}	0.117^{***}	0.117^{***}	0.092^{***}	0.083^{***}
	(0.004)	(0.009)	(0.007)	(0.007)	(0.008)
Aug (λ_{Aug})	0.011^{**}	0.042^{***}	0.042^{***}	-0.014^{+}	-0.012
	(0.004)	(0.009)	(0.008)	(0.007)	(0.009)
Sep (λ_{Sep})	-0.044^{***}	-0.025^{**}	-0.005	-0.070^{***}	-0.064^{***}
	(0.004)	(0.009)	(0.007)	(0.007)	(0.009)
Oct (λ_{Oct})	0.020^{***}	0.013	0.017^{*}	0.004	0.049^{***}
	(0.004)	(0.009)	(0.007)	(0.007)	(0.009)
Nov (λ_{Nov})	0.039^{***}	0.032^{***}	0.047^{***}	0.034^{***}	0.042^{***}
	(0.004)	(0.009)	(0.007)	(0.007)	(0.009)
Dec (λ_{Dec})	0.124^{***}	0.140^{***}	0.150^{***}	0.111^{***}	0.101^{***}
	(0.004)	(0.009)	(0.007)	(0.007)	(0.009)
$\mathbf{1}\{Year_t = 2019\}$ (Λ_{2019})	0.042^{***}	0.064^{***}	0.051^{***}	0.033^{***}	0.027^{**}
	(0.004)	(0.009)	(0.007)	(0.007)	(0.008)
$\mathbf{1}\{Year_t = 2019\}$ × Feb (ϕ_{Feb})	-0.001	-0.013	-0.002	0.009	-0.005
	(0.005)	(0.011)	(0.009)	(0.009)	(0.011)
$\mathbf{1}\{Year_t = 2019\}$ × Mar (ϕ_{Mar})	-0.022^{***}	-0.005	-0.014	-0.017^{+}	-0.048^{***}
	(0.005)	(0.011)	(0.009)	(0.009)	(0.011)
$\mathbf{1}\{Year_t = 2019\}$ × Apr (ϕ_{Apr})	0.019^{***}	0.022^{+}	0.018^{*}	0.024^{**}	0.009
	(0.005)	(0.012)	(0.009)	(0.009)	(0.011)
$\mathbf{1}\{Year_t = 2019\}$ × May (ϕ_{May})	-0.009^{+}	-0.004	-0.009	-0.009	-0.013
	(0.005)	(0.012)	(0.009)	(0.009)	(0.011)
$\mathbf{1}\{Year_t = 2019\}$ × Jun (ϕ_{Jun})	-0.035^{***}	-0.020^{+}	-0.011	-0.046^{***}	-0.057^{***}
	(0.005)	(0.012)	(0.009)	(0.009)	(0.011)
$\mathbf{1}\{Year_t = 2019\}$ × Jul (ϕ_{Jul})	0.014^{**}	0.041^{***}	0.022^{*}	0.006	-0.001
	(0.005)	(0.012)	(0.010)	(0.009)	(0.012)
$\mathbf{1}\{Year_t = 2019\}$ × Aug (ϕ_{Aug})	-0.008	0.001	-0.007	0.0003	-0.026^{*}
	(0.005)	(0.012)	(0.010)	(0.010)	(0.012)
$\mathbf{1}\{Year_t = 2019\}$ × Sep (ϕ_{Sep})	0.006	0.017	-0.007	0.012	0.005
	(0.005)	(0.012)	(0.010)	(0.010)	(0.012)
$\mathbf{1}\{Year_t = 2019\}$ × Oct (ϕ_{Oct})	0.003	-0.005	0.002	0.012	-0.002
	(0.005)	(0.012)	(0.010)	(0.010)	(0.012)
$\mathbf{1}\{Year_t = 2019\}$ × Nov (ϕ_{Nov})	-0.014^{**}	-0.012	-0.005	-0.018^{+}	-0.021^{+}
	(0.005)	(0.013)	(0.010)	(0.010)	(0.012)
$\mathbf{1}\{Year_t = 2019\}$ × Dec (ϕ_{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)
χ^2 ($\phi_{Feb} = 0, \dots, \phi_{Dec} = 0$)	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

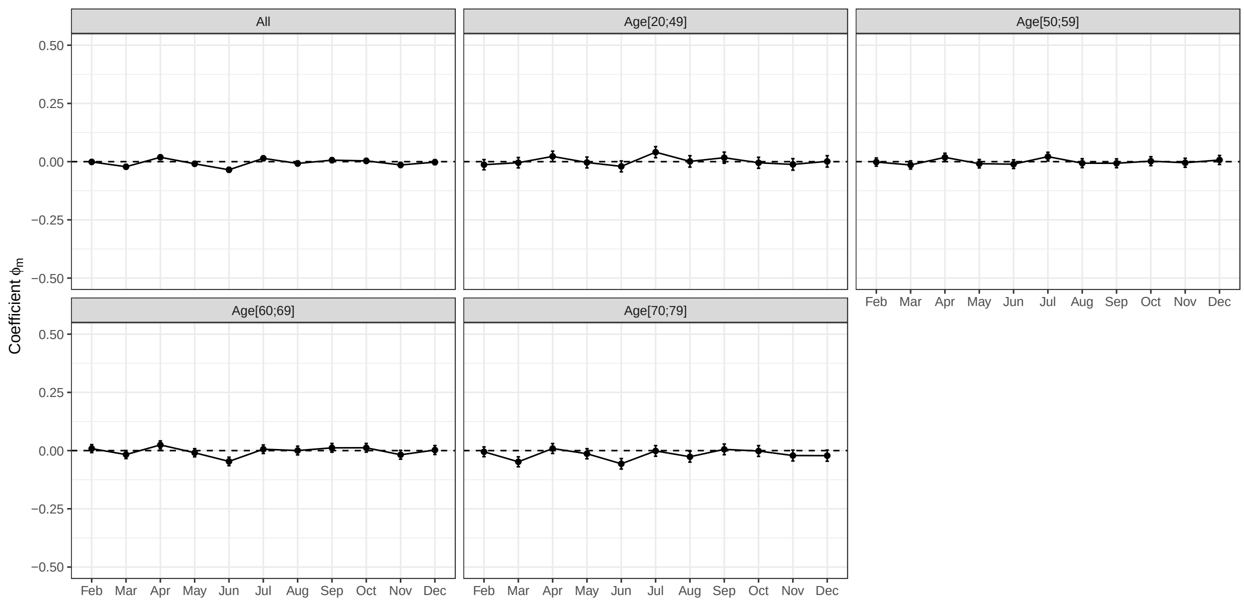

Figure 14: Seasonality effects for different age groups.

A.2 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 7) as well as a version with co-morbidity (Table 8). This split-sample by age approach allows each cohort to have different yearly growth trends and month 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.

Finally, 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 9 is the analogue of Table 12. 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.

Table 7: Impact of age on consumption expenditures

	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 $\times Year_t$ (Ψ_{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 8: Impact of age on consumption expenditures

	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 $\times Year_t$ (Ψ_{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
Cluster robust standard errors in (); Errors clustered by person

Table 9: 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$\times Year_t$ (Ψ_{it})	No	Yes	Yes	Yes
Income Group $\times Year_t$ (Ψ_{it})	No	No	Yes	Yes
Age Group $\times$ Income Group $\times Year_t$ (Ψ_{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

A.3 Model Calibration

Table 10: Impact of age on expenditures (for model calibration)

	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$\times Year_t$ (Ψ_{it})	No	Yes	Yes	Yes
Income Group $\times Year_t$ (Ψ_{it})	No	No	Yes	Yes
Age Group $\times$ Income Group $\times Year_t$ (Ψ_{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.4 Regression Tables used to Build the Figures in the Paper

Table 11: 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
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in (); Errors clustered by person

Table 12: 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 $\times Year_t$ (Ψ_{it})	No	Yes	Yes	Yes
Income Group $\times Year_t$ (Ψ_{it})	No	No	Yes	Yes
Age Group $\times$ Income Group $\times Year_t$ (Ψ_{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

Cluster robust standard errors in (); Errors clustered by person

Table 13: 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$\times Year_t$ (Ψ_{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 14: Impact of age and comorbidity on consumption expenditures (maps to figure 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$\times Year_t$ (Ψ_{it})	Yes	Yes
Income Group $\times Year_t$ (Ψ_{it})	Yes	Yes
Age Group $\times$ Income Group $\times Year_t$ (Ψ_{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