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HOW DO PEOPLE RESPOND TO SMALL PROBABILITY EVENTS WITH LARGE, NEGATIVE CONSEQUENCES?

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ABSTRACT

We study how people react to small probability events with large negative consequences using the outbreak of the COVID-19 epidemic as a natural experiment. Our analysis is based on a unique administrative data set with anonymized monthly expenditures at the individual level. We find that older consumers reduced their spending by more than younger consumers in a way that mirrors the age dependency in COVID-19 case-fatality rates. This differential expenditure reduction is much more prominent for high-contact goods than for low-contact goods and more pronounced in periods with high COVID-19 cases. Our results are consistent with the hypothesis that people react to the risk of contracting COVID-19 in a way that is consistent with a canonical model of risk taking.

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1 Introduction

A central question in economics is: how do people respond to risk? The answer to this question has fundamental implications for asset pricing, as well as many other areas of economics. One prominent explanation of the equity premium relies critically on people responding rationally to small probability events that have large consequences (see e.g. Rietz (1988), Barro (2006), and Nakamura et al. (2013)). The way in which people react to small probability events is an important issue in the literature on prospect theory (Kahneman and Tversky (2013)).

By construction, it is difficult to gather a substantial amount of data on rare events. The outbreak of a COVID-19 epidemic provides a natural experiment for how people react to small probability events with large negative consequences–dying from COVID-19.

The probability of dying from COVID-19 is low for young people, rising with age for people older than 50 (see e.g. Dowd et al. (2020)). People of all ages can reduce the probability of becoming infected by cutting expenditures on goods and services that require social contact (e.g., sports events and restaurant meals).

We study how younger and older people changed the level and composition of their consumption expenditures in response to changes over time in the risk of infection. In addition, we compare the expenditure behavior of people with and without comorbidities.

Our empirical work relies on a unique administrative data set from Portugal that includes anonymized monthly data on individual itemized consumer expenditures. The sample covers the period from January 2018 to May 2020. The data include the age, income bracket, and gender of all people in the sample, as well as the education and occupation of a subset of these people. In general, people might reduce consumption in response to the epidemic for two reasons. First, they either lost their jobs or are worried about losing their jobs because of the COVID-19 recession. Second, they want to reduce the risk of infection. Our analysis focuses on public servants' consumption behavior. Their income is likely to have been relatively unaffected by the crisis. So, their consumption behavior should primarily reflect the influence of infection risk.

In our data, older consumers reduce their spending by more than younger consumers in a way that mirrors the age dependency in COVID-19 case fatality rates. This differential spending reduction is much larger for high-contact goods than for low-contact goods and it is more pronounced in periods with a high risk of infection.

Our key empirical results are resilient to a variety of robustness checks. These checks include controlling for comorbidity (pre-existing health conditions that increase the probability of dying from COVID-19), allowing for age-cohort-specific seasonal effects and income trends, and using our empirical approach to study the behavior of retirees, another group whose income is likely to have remained relatively stable during the epidemic.

We compare our empirical results with the predictions of a canonical model of risk-taking behavior in which people have recursive preferences of the type considered by Kreps and Porteus (1978), Weil (1989), and Epstein and Zin (1991). In this model, the probability of getting infected depends on consumption activities and the probability of dying once infected increases with age. We find that this canonical model accounts well for the way in which people of different ages responded to the COVID-19 shock.

Both our empirical and model-based results are surprising in light of a 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)). Of course, it is possible that people were particularly aware of the risks associated with COVID-19 because of all the media attention devoted to the epidemic.

Our paper is organized as follows. Section 2 describes our data set. Section 3 contains our empirical results. Section 4 describes our model. Section 5 compares our empirical estimates with the implications of our model. We conclude in section 6.

2 Data

The data, obtained from Statistics Portugal (the national statistical authority), covers the period from January 2018 to May 2020. Our dataset includes anonymized data for five hundred thousand Portuguese randomly sampled from a total 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 the age, income bracket, and gender of everyone in the sample as well as the education and occupation, in 2017, for a subset of the people in the sample.

For every person in our sample, we construct total monthly consumption expenditures as well as expenditures on high- and low-contact goods and services. The latter variables are constructed using a classification of industries into high and low contact (see Tables 8 and 9 in the appendix A.1 for details). High-contact industries include, for example, Food and Beverage Service Activities. Low-contact industries include, for example, Legal and Accounting Services. We also compute individual expenditures on pharmaceutical drugs, which we use as a proxy for comorbidity.

We construct nominal consumption expenditure data using the electronic receipts that firms provide to the tax authority as part of their value-added tax (VAT) reporting. Each receipt can be matched to a particular person because it contains the person's anonymized fiscal number.[1]

Portuguese consumers have three incentives to include their fiscal number in their expenditure receipts. First, they can then deduct from their income taxes, up to a limit,

[1] Our dataset does not include information on rent expenditures, mortgage, and other personal loan payments subject to taxes other than VAT.

expenditures on health, education, lodging, nursing homes, and general-household expenditures. Second, the government rebates to consumers 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.

A person who does not have any receipts associated with their fiscal number in a given month is excluded from the dataset in that month. We also removed from the sample 21,814 persons who in 2017 were unemployed or inactive. These people are unlikely to pay taxes and so have less of an 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. The resulting dataset contains 421,337 persons and 12,218,773 person-month observations that were 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-19 recession: public servants (58,598 people) and retirees (93,839 people). [2]

Table 1 reports descriptive statistics for monthly expenses net of VAT. For public servants, average per capita monthly expenditure on consumption goods and services is 673.9 euros, of which 307.3 euros is spent on high-contact goods and services and 26.1 euros on pharmaceutical items. Interestingly, these expenditures are roughly similar for the overall sample: average per capita monthly expenditure on consumption goods and services is 618.5 euros, of which 268.5 euros is spent on high-contact goods and services and 18.2 euros on pharmaceutical drugs. Retirees have lower levels of overall expenditure.

[2] These groups overlap because we did not exclude retirees from the population of public servants.

They spend, on average, 428.4 euros on consumption goods and services, of which 204 euros is spent on high-contact goods and services and 24.6 euros on pharmaceutical items.

Table 2 reports the same statistics as Table 1 broken down by age and income group. As explained in section 3.1, we group people according to their ages so that they have a similar risk of death from COVID-19. Our estimates of this risk are based on the statistics reported by the Portuguese health authority (DGS). Income groups are based on the 2017 income-tax brackets used by Portugal's Internal Revenue Service (IRS).[3]

3 Empirical results

This section is divided into two parts. In the first subsection, we provide a brief overview of the course of the epidemic in Portugal and the containment measures introduced by the government. We also discuss COVID-19 case-fatality rates by age and the evolution of per capita consumption expenditures in our sample. In the second subsection, we present formal econometric results of how the consumption expenditures of people with different ages and comorbidity conditions reacted to the COVID-19 shock.

3.1 The epidemic in Portugal

Figure 1 depicts the weekly time series of infected people and COVID-19 deaths in Portugal. For convenience, we refer to March, April and May of 2020 as the epidemic months. Consistent with the facts documented by Atkeson, Kopecky and Zha (2020) for a cross section of countries, the growth rate of deaths from COVID-19 fell from initially high values to substantially lower levels.

The timeline of containment measures implemented by the Portuguese government is as follows. On March 18, 2020, the government declared a state of emergency, restricting

[3]See the official website of the Portuguese IRS for additional details on income-tax brackets for 2017

movement between municipalities, closing all airports to civil transportation, and imposing border controls. On May 2, the government ended the state of emergency and began a phased reopening of the economy. On May 4, small businesses reopened. On May 18, cafés, medium-sized street stores, some museums, nurseries and the last two years of the secondary school reopened. The use of masks and social distancing became mandatory in public closed spaces.

Table 3 displays case-fatality rates (the ratio of COVID-19 deaths to people infected) by age cohort for Portugal. For comparison, we also include data for South Korea which was amongst the first countries to administer a large number of random tests.[4] Because many infected people are asymptomatic, random tests are key to estimating the number of infected people in the population (the denominator of the case-fatality rate).

Three key results emerge from Table 3. First, people in the age group 20 to 49 all have low case fatality rates. For this reason, we group these people in the same age cohort in our empirical work. Second, case fatality rates rise non-linearly with age for people older than 50. Third, while not identical, the data from Portugal and South Korea have similar implications for the impact of age on case fatality rates.

Figure 2 depicts the average logarithm of public servants' monthly consumption expenditures in January, February, March, April, and May of 2018, 2019 and 2020. Because of the large sample size, the 95 percent confidence intervals are indistinguishable from the displayed point estimates. Figures 3 is the analogue of Figure 2 for high- and low-contact consumption goods and services.

Three features emerge from Figures 2 and 3. First, there is a clear seasonal pattern that is similar in 2018 and 2019. Second, there is growth in per capita spending prior to the COVID-19 shock. Our econometric procedure takes both of these features into account in

[4]By August 3, 2020 the number of tests per confirmed cases is 253 in South Korea (South Korean Center for Disease Control and Prevention). In Portugal, this number is 64 (Statistics Portugal).

creating a counterfactual for what spending would have been in 2020 absent the COVID-19 shock. Third, there is a pronounced drop in consumption during the epidemic months. This drop for high-contact goods is much larger than for low-contact goods.

3.2 Age and the impact of COVID-19 on consumer expenditures

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

$$
\begin{aligned}
log(Expenses_{it}) = & \sum_{y=2019}^{2020} \Lambda_y \mathbf{1}\{Year_t = y\} + \sum_{m=Feb}^{May} \lambda_m \mathbf{1}\{Month_t = m\} + \boldsymbol{\theta_i} + \boldsymbol{\Psi_{it}} + \\
& \sum_{m=Mar}^{May} \Delta_m After_t \times \mathbf{1}\{Month_t = m\} + \\
& \sum_{m=Mar}^{May} \sum_{g \in AgeGroup \setminus [20;49]} \delta_{mg} After_t \times \mathbf{1}\{Month_t = m\} \times \mathbf{1}\{AgeGroup_i = g\} + \epsilon_{it}
\end{aligned}
\tag{1}
$$

Subscripts i and t denote person i and calendar month t, respectively. $After_t$ is a dummy variable equal to one in epidemic months and zero otherwise. The coefficients Λ_y measure trend growth, common across people, in year-y consumption expenditures. The coefficients λ_m control for seasonality in consumption for the months included in the sample (January through May). 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. The variable ϵ_{it} is the idiosyncratic error term. The coefficients Δ_m capture the change in spending of people in the reference group (aged 20-49) during epidemic month m. The coefficient δ_{gm} measures the additional change in spending for age group g in epidemic month m. The focus of our analysis is on the differential response of consumption by people with different ages.[5] We estimate equation 1 using a fixed effects (FE) estimator.[6] We cluster standard errors by person, as suggested in Bertrand, Duflo and Mullainathan (2004).

As long as the inflation rate for the consumption baskets of different age cohorts is the same, any inflation effects cancel out from the nominal differential response and we are left with the real differential response.

Figure 4 displays the results obtained from estimating equation 1 (see column 6 of table 4 for parameter estimates). The bars around the point estimates represent 95 percent confidence intervals. Our key findings are that all consumers reduced their expenditures during the epidemic months. But 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.

In March, when the number of cases was still low, people with ages 20-49 and those in their 50s, 60s and 70s cut their expenditures by 9.4, 11.0, 14.4 and 21.4 percent, respectively. In April, when the number of cases peaked, people with ages 20-49 and those in their 50s, 60s and 70s cut their expenditures by 29.1, 31.2, 41.1 and 50.9 percent. In May, as the number of cases fell, people with ages 20-49 and those in their 50s, 60s and 70s cut their expenditures by 19.2, 19.1, 26.0 and 32.8 percent. In all three months, the differences between the expenditure cuts of consumers older than 60 and those younger than 49 are statistically significant at a 0.1 percent level (see column 6 of table 4).

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

[6] Because of our large ample 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).

3.3 Expenditures on high- and low-contact goods and services

A natural question is whether the containment measures imposed by the government explain the differential sensitivity of consumption expenditures by age. The answer would be yes to the extent that those measures affect consumption goods predominantly consumed by older people.

Imagine that containment was the only driver of the change in consumption expenditures on high-contact goods during the epidemic months. Then, the percentage decline in high-contact consumption expenditures should be the same for people of different ages. Suppose that, in reality, older people cut their expenditures on high-contact goods by more than younger people. Then, we would infer that age-dependency in consumption patterns was primarily driven by the risk of infection.

Motivated by these considerations, we analyze how consumption expenditures on high- and low-contact goods and services change as a function of people's age. Some consumers have zero expenditures on high-contact goods in some of the epidemic months. In addition, the distribution of expenditures features overdispersion, i.e. the conditional variance is larger than the conditional mean. For these reasons, we adopt a negative-binomial version of regression model 1 with fixed effects (see Allison and Waterman (2002) and Guimaraes (2008)) in which the dependent variables are the individual expenditures on high- and low-contact goods and services.[7]

Our key results are displayed in Figure 5 and reported in Table 5. This figure shows that older cohorts cut their expenditures on high-contact goods and services by much more than younger cohorts in all epidemic months. The differences between the expenditure cuts of consumers older than 60 and those younger than 49 are statistically significant at

[7]We estimate our model using the *fixest* R routine discussed in Bergé et al. (2018). This routine is efficient and handles large samples in a reasonable amount of time.

a 0.1 percent level.

For example, when infections peaked in April, consumers in their 70s cut their expenditures by 61.8 and 28.4 on high- and low contact good, respectively. The corresponding cut in expenditures for people younger than 49 is 26.0 and 19.2, respectively. Older cohorts cut their expenditures more aggressively than younger cohorts in all of the epidemic months. These cuts are particularly pronounced in April.

Overall, the results in Table 5 support the view that age-dependency in consumption patterns during the epidemic months was driven by the risk of infection.

3.4 The response of people with different income

The economic model discussed below implies that, in order to reduce the risk of infections, high-income people cut their expenditures by more than low-income people. The reason, according to the logic of the model discussed in Section 4, is that the rich have more to lose from becoming infected than the poor. Since older people might have higher income than younger people, our results might conflate the effect of age per se with the effect of income.

Figure 6 reports the results of estimating equation 1 for separate income groups. This procedure allows for separate time trends in the expenditures of each income group. Two key results emerge from figure 6. First, for people in every income group, on average over the epidemic months, those older than 60 cut expenditures by more than those younger than 49. For all income groups, the contrast between between younger and older people is largest in April. For example, for people in the medium income group, those in the 60-69 and 70-79 age cohorts cut their expenditures, relative to people younger than 49, by 9.0, and 19.1 percent, respectively. Second, conditional on people's age, the higher is their income, the larger is the decline in their consumption expenditures. For example, people in the low-, medium- and high-income group who are between 60 and 69 years old cut their expenditures, by 5.7, 9.0, and 10.9 percent more than people younger than 49.

The finding that expenditure cuts are an increasing function of income complements the evidence in Chetty et al. (2020) and Carvalho et al. (2020). Unlike these authors, we observe people's income, so we do not have to rely on home-address ZIP codes to proxy for that income.

3.5 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-19.[8] A natural question is whether people with comorbidities react to that risk by reducing consumption more than people who do not have comorbidities.

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

Our key result is displayed in Figure 7 and reported in Table 7. People with comorbidities cut their consumption by more than people without comorbidities. For example in April, at the peak of the infection, people younger than 49 with no comorbidities cut their consumption by 30 percent. In contrast, people younger than 49 who have comorbidities dropped their consumption expenditures by 37.4 percent.

We find no statistically significant interaction between age and comorbidity: the impact

[8] 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.

of comorbidity is the same for young and old people.

Interestingly, even after controlling for comorbidity, age continues to be an important driver of consumption behavior. On average, during the epidemic months, people younger than 49 with no comorbidities cut their expenditures by 19.6 percent. People with no comorbidities who are in their 50s, 60s and 70s cut consumption expenditures on average during the epidemic months by an additional 0.5, 6.6 and 13.3 percent, respectively.

Taken together, these results provide additional support for the view that people's consumption decisions respond to the risk of dying from COVID-19.

3.6 Robustness

In the appendix, we report the results of four robustness checks. First, in our benchmark specification we assume the seasonal effects for January through May 2020 are the same as the common seasonal effects in 2018 and 2019. We provide evidence of the empirical plausibility of this assumption.

Second, we re-do our benchmark analysis allowing for different year-on-year expenditure trends for each age cohort. We find a similar pattern for the impact of age on the response of expenditures to the COVID-19 shock.

Third, we provide estimates for how different age groups changed their overall consumption expenditures and spending on high-contact and low-contact sectors of the economy using an alternative to the negative-binomial specification. This alternative is the Poisson pseudo-maximum likelihood estimation with fixed effects proposed by Silva and Tenreyro (2011). We find that our results are robust to this alternative.

Fourth, we re-do our main empirical analysis for retirees as opposed to public servants. Retirees are another group of people whose income is likely to have remained relatively stable during the epidemic. Our results are similar to those that we obtain for public servants.

4 A model of risk-taking behavior

We focus our model-based analysis on two questions. First, are people's consumption decisions consistent with a standard model of risk-taking behavior? Second, what fraction of the drop in consumption was due to people's risk-avoidance behavior as opposed to the containment measures imposed by the government? To answer these questions, we use a partial-equilibrium approach which allows us to confront people of different ages and health status with real wages, real interest rates, and probabilities of infection that mimic those observed in the data using a minimal set of assumptions.

We divide the population into two groups: old and young. To simplify, we assume that young people become old with a constant probability per period. This stochastic-aging assumption makes the model more tractable because it allows us to consider only two age groups. With deterministic aging, we would need to keep track of all the different age groups between ages 20 and 80.

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. The critical difference between old and young people is the risk of dying from COVID-19 or from other causes.

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 preference specification is that it separates the coefficient of relative risk aversion from the elasticity of intertemporal substitution. Córdoba and Ripoll (2017) make a cogent case for the use of this class of preferences when studying mortality risk. To simplify the notation, we omit time subscripts.

The symbols x and x' denote x_t and x_{t+1}, respectively. Each time 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. Each person faces the budget constraint

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

where c_a^h is the consumption of a person of age a and health status h, w is the real wage rate, and b_a is the amount invested in an asset that yields a real interest rate r by a person in age group a. As in Eichenbaum, Rebelo and Trabandt (2020), we model the containment measures imposed by the government as a Pigouvian tax rate on consumption denoted by μ.

The probability that a person in age group a becomes infected at time t, τ_a, is given by the transmission function:

$$\tau_a = \pi_1 c_a^h I + \pi_2 I, \tag{2}$$

where I is the number of infected people in the population at time t. The terms $\pi_1 c_a^h I$ and $\pi_2 I$ represent the probability of becoming infected through consumption- and non-consumption related activities, respectively. As in Eichenbaum, Rebelo and Trabandt (2020), this function embodies the assumption that people meet randomly in consumption- and non-consumption-related activities and that susceptible people can reduce their infection probability by cutting their consumption.

We assume that utility takes the constant-elasticity form of the Kreps and Porteus (1978) recursive preferences considered by Weil (1989) and Epstein and Zin (1991). The lifetime utility of a person with age a and health status h is

$$U_a^h = z + \left[(1-\beta)(c_a^h)^{1-\rho} + \beta \left\{ E\left[\left(U_a^h \right)' \right]^{1-a} \right\}^{(1-\rho)/(1-\alpha)} \right]^{1/(1-\rho)}.$$

Here, z is a constant that influences the value of life (see Hall and Jones (2007)), β 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 the standard time-separable expected discounted utility. The expectations operator E, takes into account all the stochastic elements of the environment, including the possibility of death.

Below, we describe the value functions of different people. We denote by π_{ad} the probability that a person of age a dies after becoming infected. The value functions of susceptible people have two state variables: their asset balance and the total number of infected people in the economy. The latter is relevant because it affects the risk of susceptible people becoming infected (see equation (2)). The value functions of susceptible and recovered people depend only on their asset balance.

The value function of a young susceptible person, $U_y^s(b, I)$, is

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

where δ_y is the probability of dying from non-viral causes. Recall that v is the probability of a young person becoming old. U_y^i and U_o^i are the value functions of a young and old infected person, respectively.

The function $B(b')$ represents the utility from leaving a bequest b' upon death. We assume that this function takes the form:

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

where $\theta_0 > 0$ and $\theta_1 > 0$. The presence of a bequest motive allows the model to be consistent with three empirical observations. First, many people die with large amounts of assets (see e.g. Huggett (1996) and De Nardi and Yang (2014)). Second, the consumption expenditures of older 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 $\theta_0 > 0$.

With probability $1 - \delta_y - v$, a young susceptible person survives without aging. With probability τ_y, this person remains young but becomes infected. With probability $1 - \tau_y$, the person remains young and susceptible. A young person ages with probability v. With probability τ_y, this person becomes old and infected. With probability $1 - \tau_y$, the person remains susceptible but becomes old.

The value function of an old, susceptible person, $U_o^s(b, I)$, is

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

where δ_0 is the probability of dying from non-viral causes. With probability $(1-\tau_o)(1-\delta_o)$, this person survives and does not get infected, remaining a susceptible old person. With probability $\tau_o(1-\delta_o)$, the person survives but gets infected, becoming an infected old person.

The value function of a young, infected person, $U_y^i(b)$, is

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

A young, infected person survives without aging with probability $1-\delta_y-v$. With probability $1-\pi_{yr}-\pi_{yd}$, the person remains young and infected. With probability π_{yr}, the person remains young and recovers. With probability π_{yd}, the person remains young but dies from the infection. With probability $1-\tau_y$, the person remains young and susceptible. A young person ages with probability v. With probability $(1-\pi_{yr}-\pi_{yd})$, the person becomes old but remains infected. With probability π_{yr}, the person becomes old and recovers. With probability π_{yd} the person becomes old and dies from the infection.

The value function of an old infected person, $U_o^i(b)$, is

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

With probability $(1-\pi_{or}-\pi_{od})(1-\delta_o)$, this person survives but does not recover, remaining an old infected person. With probability $\pi_{or}(1-\delta_o)$, the person survives and recovers. This person dies with probability δ_o and $(1-\delta_0)\pi_{or}$ from non-viral causes and viral causes, respectively.

The value function of a young recovered person, $U_y^r(b)$, is

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

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, $U_o^r(b)$, is

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

4.1 Model calibration

We now discuss the parameter values used to calibrate the model. We set the annual real interest rate, r, to 1 percent which corresponds roughly to the realized real yield on 10-year Portuguese government bonds over the period March to May, 2020. We use the life-expectancy tables produced by Statistics Portugal to calibrate non-COVID-related mortality rates for young and old people. Consistent with Portuguese demographic data, we assume that the fraction of the population between 20 and 59 years old is equal to 70 percent of the population between 20 and 79 years old. We set the probability of aging so that the implied average age difference between old and young people is the same as in the data (28 years).

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 are consistent with those used by Albuquerque et al. (2016) to account for the equity premium and other properties of financial-markets data. This type of data is relevant to our analysis because it reflects 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, Eichenbaum and Evans (2005)).

The level parameter in the utility function (z) and the two parameters that control the utility of bequests (θ_0 and θ_2) are chosen so that the model is consistent with three features of the Portuguese data. First, the ratio of young to old 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)).

As in Eichenbaum, Rebelo and Trabandt (2020), we choose the parameters of the transmission function (see equation (2)) to be consistent with the so-called Merkel scenario.

According to this scenario, 60 percent of the population would be eventually exposed to the virus if consumption remains constant at pre-epidemic levels.[9] Our parameter values are consistent with Ferguson et al. (2006)'s finding that 1/3 of airborne infections come from economic interactions and 2/3 from non-economic interactions. As in Atkeson (2020), we assume that it takes 18 days to either die or recover from an infections. Consistent with the case-mortality rates for Portugal reported in Table 1 of the appendix, we assume that the case fatality rates are 0.5 percent for those younger than 60 and 3 percent for those older than 60.

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 a year.

We described the timeline of containment measures implemented by the Portuguese government in section 3.1. According to INE (2020), the percentage of firms that remained open, even if only partially, is 83, 91 and 96 percent in April, May, and June, respectively. These percentages are similar for both small and large firms, so they are likely to be a good measure of the impact of containment measures on the supply of goods and services. Accordingly, we use the share of businesses that closed during the lockdown as an admittedly noisy proxy for the containment rate.

4.2 Estimating COVID-19 deaths and cases for Portugal

People in the model must compute the probability of getting infected at each point in time. Those probabilities depend on the number of infected people. In solving the model, we input the time series for the number of infected people from the data.

There is considerable measurement error in official measures of total infections and

[9]This scenario was outlined by Angela Merkel in her March 11, 2020 speech, see "Merkel Gives Germans a Hard Truth About the Corona Virus", New York Times, March 11, 2020.

deaths due to COVID-19. For this reason, we estimate total deaths due to COVID-19 and use an estimate of the case-fatality rate to back out the time series for total infections.

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

Our time-series model for deaths in the absence of COVID-19 is the Bayesian model proposed by Scott and Varian (2014); Brodersen et al. (2015) and implemented in the CausalImpact R package developed at Google Brodersen et al. (2015). This model has a state equation that relates the observed data to a vector of latent variables and a transition equation that describes how the latent state evolves through time. We collected data from January 2014 to August 2020 from the Portuguese real-time death reporting system DGS (n.d.). We aggregate daily reported deaths to construct weekly time series of death counts for people younger and older than 60.

We estimated the model using data from April 2014 to May 2019. Figure 8 plots historical deaths by week of the year. Zero denotes the first week of the year. The dashed vertical grey line marks the first week of March. The dashed vertical black line marks the week that corresponds to the beginning of Portugal's lockdown period in 2020. Figure 9 plots actual deaths from April 2019 to August 2020 (blue line) and predicted deaths absent COVID-19 (orange line). Our estimate of the COVID-19-related deaths is the difference between the blue and the orange lines in March, April and May, 2020.

5 Comparing empirical estimates with model implications

To compare the model's implications with the data, we estimate a version of the benchmark regression with only two groups, younger and older than 60. Our estimates, reported in Appendix A.4, imply that people younger than 60 cut consumption expenditures by 10.4, 30.4, and 19.1 percent in March, April and May, respectively. People older than 60 cut expenditures by 17.5, 45.3, and 28.9 percent in March, April and May, respectively.

Turning to the model, Panel A of figure 10 shows the optimal consumption decisions during the epidemic months for people with different asset levels. Time matters for two reasons: both the probability of becoming infected and containment rates vary over time. The right- and left-hand figure pertains to old and young consumers, respectively. The model does well at accounting for our empirical findings. First, the old reduce their consumption by more than the young. The reason is that the risk of dying from an infection is much larger for an older person. Second, richer consumers cut their consumption by more than poorer consumers. The reason is that richer people have more to loose in terms of lifetime utility. This effect is much more important for old consumers because their probability of dying from infection is much larger.

According to the Survey of Household Financial Conditions (Costa and Farinha, 2012), the average net wealth for Portuguese households over the period 2013-2017 is about 150 thousand euros. Based on an average of two adults per household, per capita net wealth is 75 thousand euros. We report the model's predictions for people with this level of assets.

In the model, consumption of the young falls by 13, 30 and 18 percent in March, April and May, respectively. Our data-based estimates of the corresponding fall in the consumption of the young are 10 percent, 30 percent, and 19 percent. In the model, consumption of the old falls by 29, 42 and 27 percent in March, April and May, respectively. Our data-based estimates of the corresponding consumption falls are 17 percent, 45 percent, and 29 percent.

Our model does quite well at accounting for the behavior of young people during all of the epidemic months and the behavior of old in April and May. The model overpredicts the consumption response of old people in March. This property could reflect the slow diffusion of information about the fatality risk associated with COVID-19 in the beginning of the epidemic.

An important question is: what was the impact on consumption of containment measures versus people's risk aversion to becoming infected? A natural way to answer this question is to re-solve the model setting containment rates to zero. But, to do this one would have to construct the counterfactual path for aggregate infections that would obtain in the absence of containment. This counterfactual is hard to construct without a general equilibrium model. But building such a model would require a host of additional assumptions.

We adopt the following alternative strategy: 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.

Panel B of figure 10 shows how the consumption decision rules for old and young people vary over time in the absence of infections for different asset levels. Time is relevant because containment rates vary over time. Panel B shows that the containment measures in isolation have a similar impact on the consumption of young and old. So, the pronounced difference in the expenditures of young and old displayed in Panel A of Figure 10 reflects mostly people's response to their risk of dying from COVID-19. This conclusion is consistent with the findings of Villas-Boas et al. (2020) and Goolsbee and Syverson (2020) based on mobility data. It is also consistent with the conclusions in Chetty et al. (2020).

The difference between the decision rules displayed in panel A and B of figure 10 gives us the reduction in spending that would have obtained in the absence of containment. For example, these panels imply that the consumption of young and old people would have dropped in April by 9.2 and 21.2 percent, respectively, had there been no containment. So while containment had some effect, much of the difference in the behavior of young and old people reflects their response to the risks of becoming infected.

In sum, our empirical findings are broadly consistent with a standard model of risk-taking behavior. The key prediction of the model is that people reduce their consumption to lower the probability of getting infected, even in the absence of containment. Older people cut their consumption by more than younger people because their risk of dying from COVID-19 is higher.

6 Conclusion

This paper studies how people respond to low probability events that have large consequences. We find strong evidence that people react to such risks in a way that is consistent with a canonical model of risk taking.

Low-probability events play an important role in many economic models and are the focus of many policy debates on topics such as global warming and terrorism. How to model people's behavior with respect to such events remains a controversial issue. After all, it is hard to learn about the probability of rare events. Our empirical results suggest that, at least for events that receive a great deal of media attention, people respond in a way that is commensurate with the risks they face.

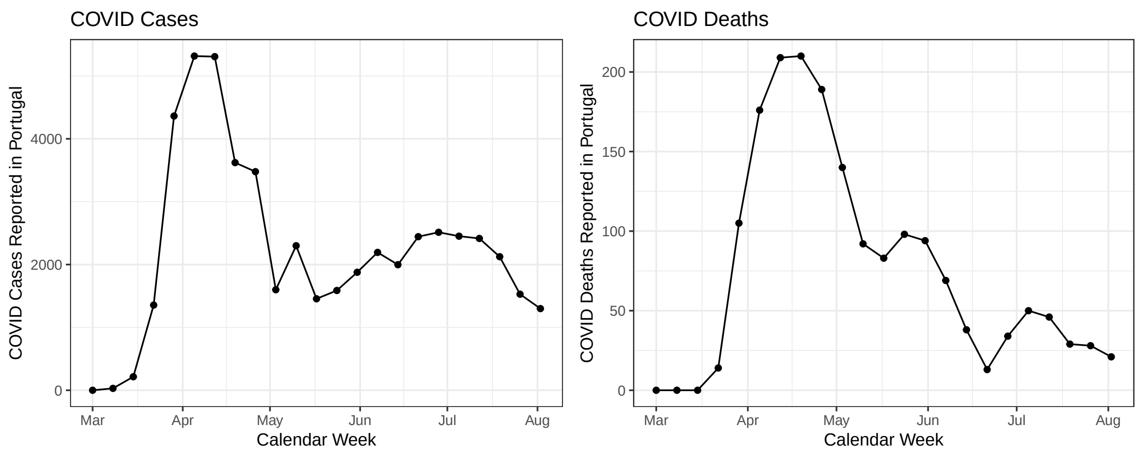

Figure 1: COVID-19 cases and deaths reported by the Portuguese Health Authority (August 5, 2020).

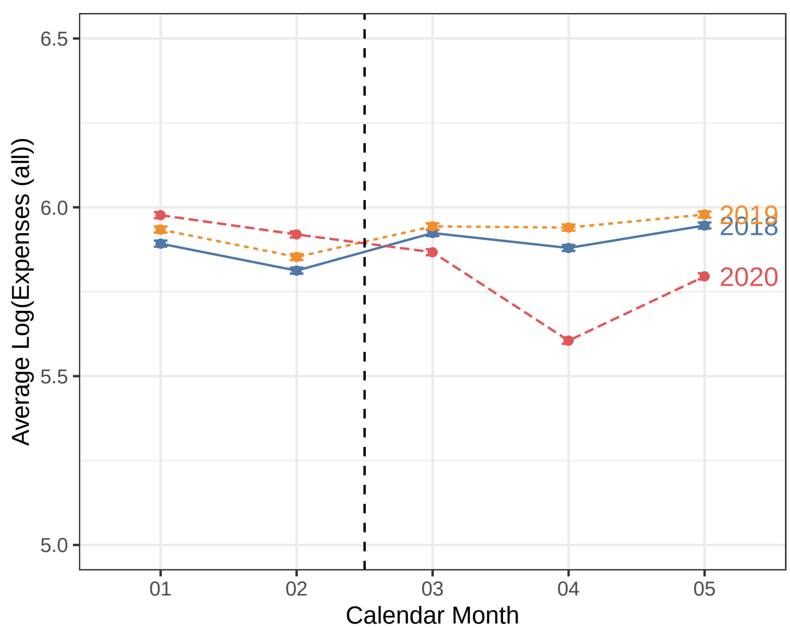

Figure 2: Average of the logarithm of public servants' monthly expenditures

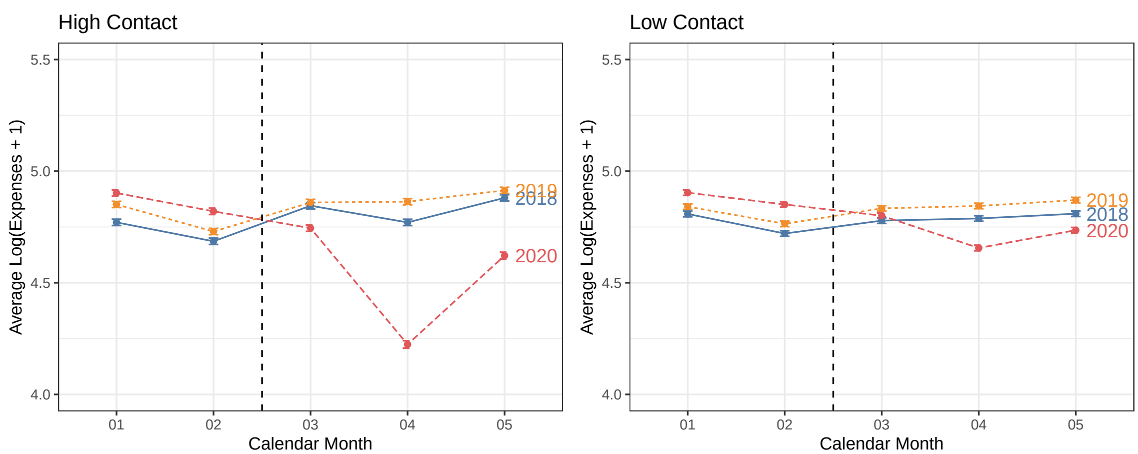

Figure 3: Average of the logarithm of public servants' monthly expenditures on high- and low- contact goods and services

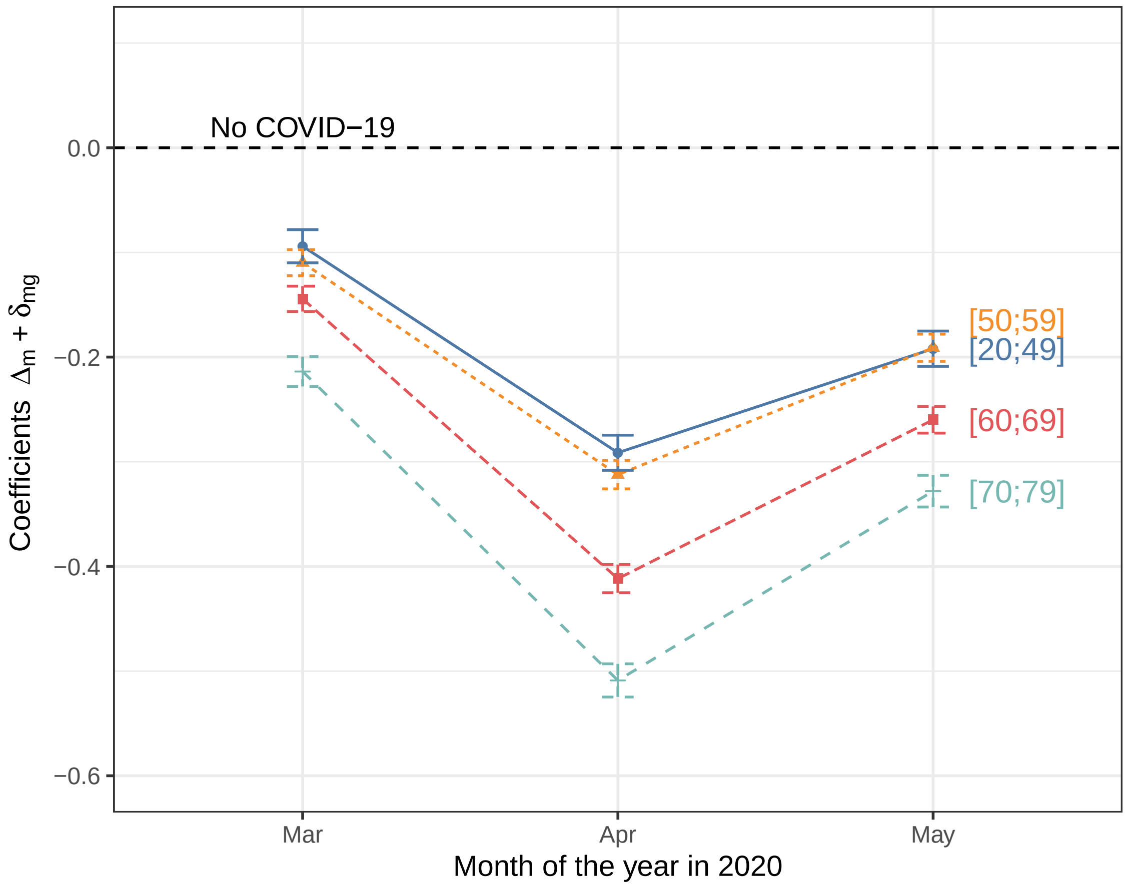

Figure 4: Changes in expenditures of public servants during the epidemic relative to a counterfactual without COVID-19.

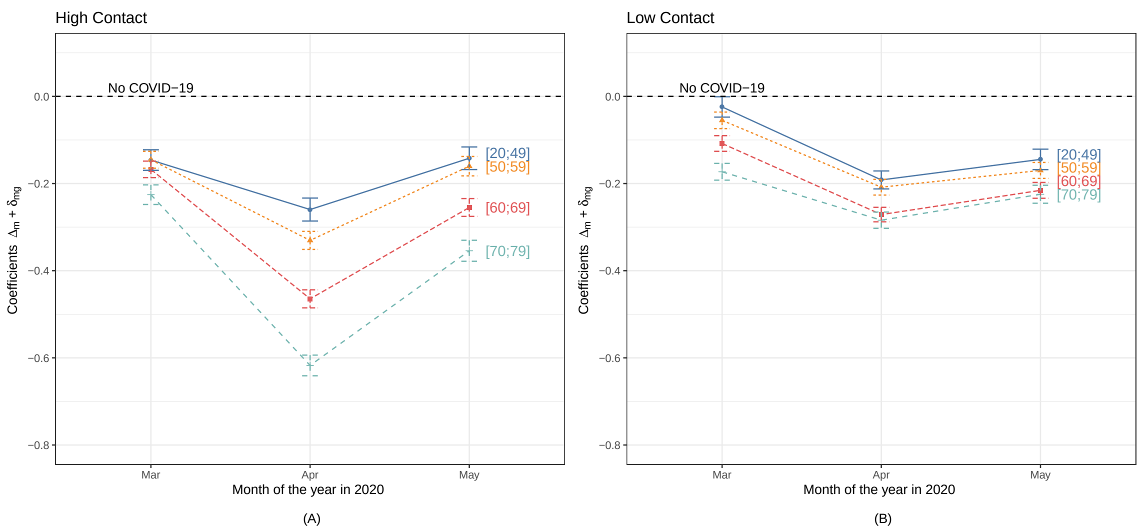

Figure 5: Changes in expenditures of public servants during the epidemic relative to a counterfactual without COVID-19. Panel (A) and (B) pertain to high- and low-contact goods and services, respectively.

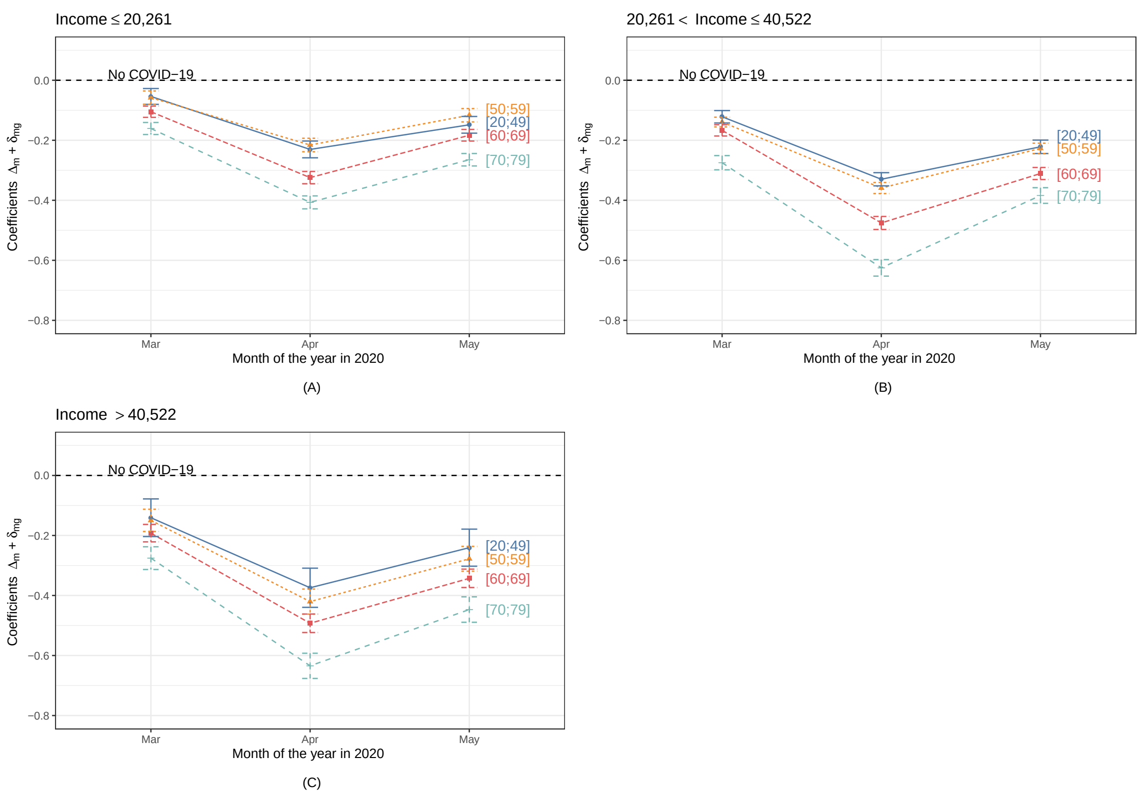

Figure 6: Changes in expenditures of public servants in different income groups during the epidemic relative to a counterfactual without COVID-19.

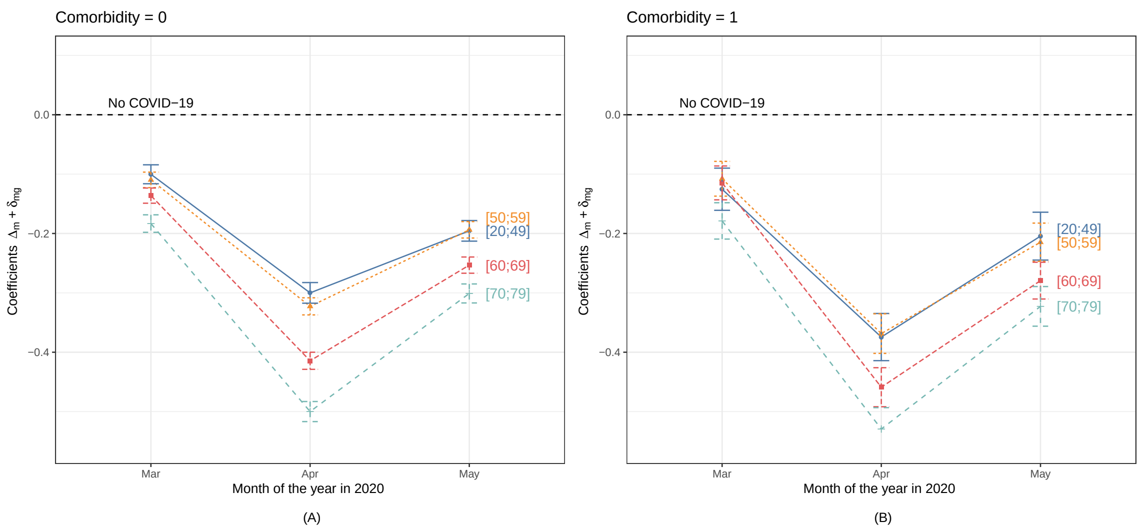

Figure 7: Changes in the expenditures of public servants during the epidemic relative to a counterfactual without COVID-19 for people with and without comorbidity.

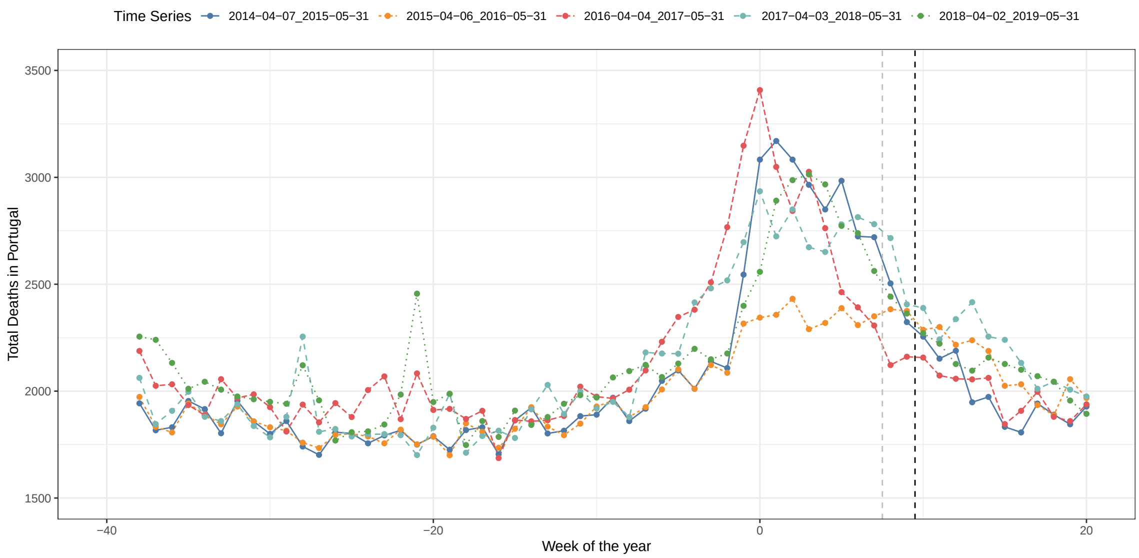

Figure 8: Actual deaths in Portugal from 2014 to 2019

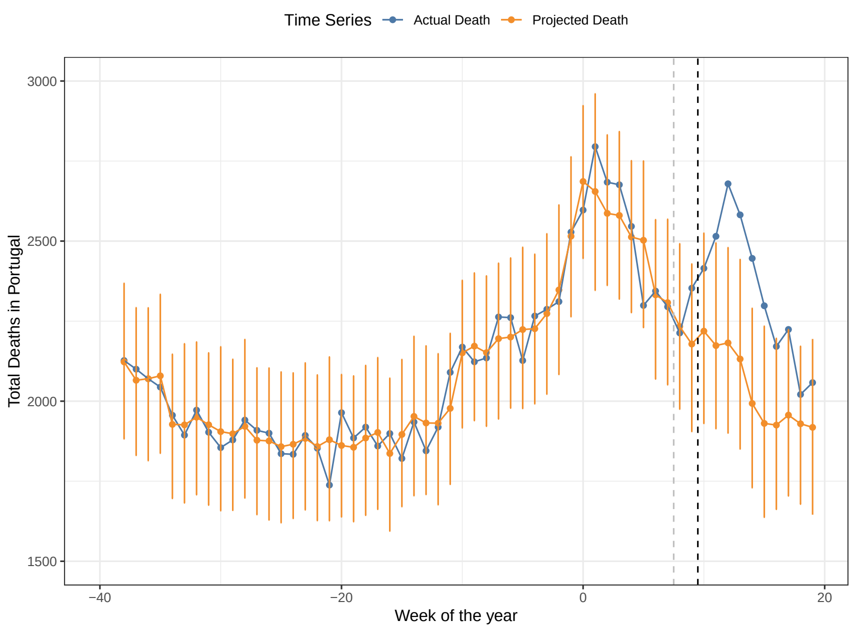

Figure 9: Actual deaths and predicted deaths absent COVID-19 in Portugal from April 2019 to May 2020

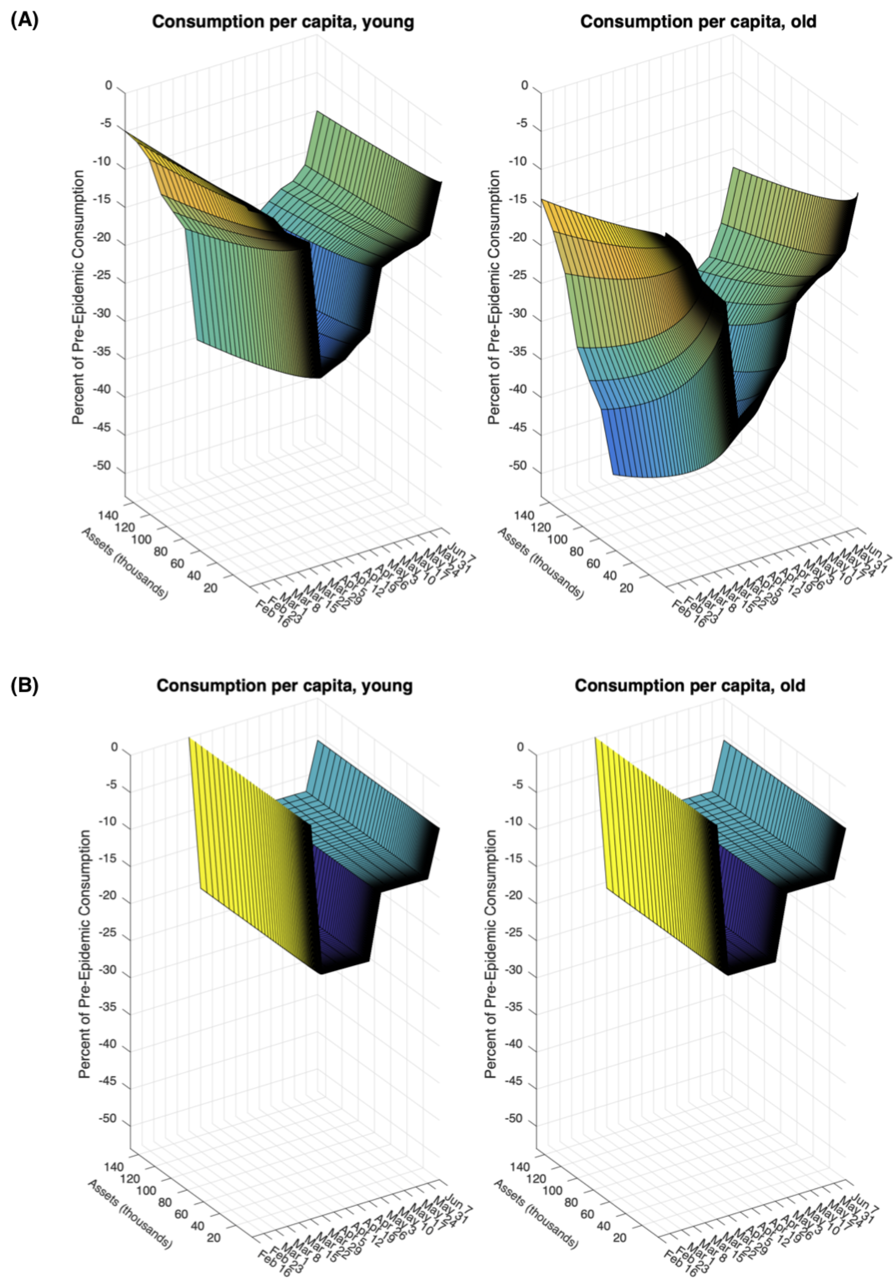

Figure 10: Consumption decision rules for old and young implied by economic model. Panel A shows the combined effect of the epidemic and containment measures. Panel B shows the effect of containment measures only.

Table 1: Descriptive statistics, January 2018 - May 2020

Statistic	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
All People					
Expense p. month (All)	618.5	2,125.3	120.8	283.3	568.1
Expense p. month (High Contact)	268.5	984.3	19.6	101.6	280.5
Expense p. month (Low Contact)	282.4	1,295.7	43.4	120.4	266.4
Expense p. month (Pharmacy)	18.2	35.9	0.0	4.8	24.3
Public Servants					
Expense p. month (All)	673.9	1,639.4	211.4	417.7	731.8
Expense p. month (High Contact)	307.3	554.5	64.0	191.9	396.4
Expense p. month (Low Contact)	297.1	1,046.4	68.7	158.9	315.7
Expense p. month (Pharmacy)	26.1	43.4	0.0	11.8	36.1
Retirees					
Expense p. month (All)	428.4	1,659.5	78.8	187.5	411.0
Expense p. month (High Contact)	204.0	834.7	14.8	70.5	214.1
Expense p. month (Low Contact)	189.8	974.3	26.1	81.4	176.0
Expense p. month (Pharmacy)	24.6	42.4	0.0	12.5	35.0

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

Table 2: Distribution of monthly expenses by age and income, January 2018 - May 2020

Group	N	Mean	St. Dev	Pctl(25)	Median.	Pctl(75)
All People						
Age $_{[20;49]}$	190,0336	632.9	2,015.0	135.8	311.3	589.7
Age $_{[50;59]}$	85,305	668.1	2,365.8	122.2	298.3	611.2
Age $_{[60;69]}$	74,390	605.5	2,220.6	97.6	246.9	539.1
Age $_{[70;79]}$	71,605	425.7	1,800.3	65.2	169.6	389.0
Income $_{[0;7,091]}$	114,295	286.7	1071.9	43.8	125.7	287.3
Income $_{]7,091;20,261]}$	217,381	471.4	1405.5	123.1	265.4	489.0
Income $_{]20,261;40,522]}$	64,593	894.3	2061.3	310.9	549.6	907.4
Income $_{]40,522;80,640]}$	19,377	1549.3	3145.0	461.9	831.7	1486.4
Income $_{\geq 80,640}$	5,691	5227.0	10802.9	683.1	1588.7	5439.4
Public Servants						
Age $_{[20;49]}$	10,007	769.8	1,904.5	288.2	501.3	798.0
Age $_{[50;59]}$	15,367	716.5	1,610.8	253.0	473.6	789.8
Age $_{[60;69]}$	18,837	660.3	1,612.7	193.8	393.6	712.9
Age $_{[70;79]}$	14,387	550.1	1,457.7	143.3	308.3	597.0
Income $_{[0;7,091]}$	1,620	250.2	861.6	52.1	125.7	263.3
Income $_{]7,091;20,261]}$	24,250	428.0	1,106.0	139.0	275.1	483.1
Income $_{]20,261;40,522]}$	25,651	757.0	1,659.8	299.8	520.4	824.6
Income $_{]40,522;80,640]}$	6,194	1,124.6	2,272.8	433.9	746.1	1,196.5
Income $_{\geq 80,640}$	883	2,148.9	4,443.7	625.8	1,122.7	1,963.2
Retirees						
Age $_{[20;49]}$	935	229.5	951.2	16.9	78.0	206.2
Age $_{[50;59]}$	3,114	283.2	1,119.1	31.7	108.2	277.6
Age $_{[60;69]}$	26,920	420.1	1,434.7	76.0	195.7	430.1
Age $_{[70;79]}$	63,467	411.8	1,722.5	65.8	170.0	386.2
Income $_{[0;7,091]}$	37,998	159.7	580.3	26.9	78.9	171.0
Income $_{]7,091;20,261]}$	38,328	353.2	940.0	105.1	214.0	396.7
Income $_{]20,261;40,522]}$	13,925	722.5	1,674.3	245.5	459.0	783.1
Income $_{]40,522;80,640]}$	3,351	1,299.3	2,538.1	417.1	760.4	1,345.9
Income $_{\geq 80,640}$	834	5,423.6	11,681.5	689.8	1,652.5	5,527.1

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

Table 3: Case-fatality Rates, COVID-19

	Age Group	Infected	Deceased	Case Fatality Rate
Portugal				
	$[0; 19]$	4,034	0	0.0%
	$[20; 49]$	24,230	24	0.1%
	$[50; 59]$	7,628	55	0.7%
	$[60; 69]$	5,053	152	3.0%
	$[70; 79]$	3,505	332	9.5%
	≥ 80	5,781	1,155	20.0%
South Korea				
	$[0; 19]$	890	0	0.0%
	$[20; 49]$	6,495	5	0.1%
	$[50; 59]$	2,275	15	0.7%
	$[60; 69]$	1,653	41	2.5%
	$[70; 79]$	846	82	9.7%
	≥ 80	556	139	25.0%

Source: Data for Portugal collected from the Portuguese Health Authority on July 28, 2020. Data for South Korea collected from the South Korean CDC on June 28, 2020.

Table 4: Impact of age on consumption expenditures

	Dependent variable:					
	$log(Expenses_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$After_t$ (γ_0)	-0.259^{***}	-0.194^{***}	-0.192^{***}			
	(0.003)	(0.006)	(0.006)			
$After_t \times \mathbf{1}\{Age_i = [50;59]\}(\gamma_{[50;59]})$		-0.013^{+}	-0.012			
		(0.007)	(0.008)			
$After_t \times \mathbf{1}\{Age_i = [60;69]\}(\gamma_{[60;69]})$		-0.080^{***}	-0.079^{***}			
		(0.007)	(0.007)			
$After_t \times \mathbf{1}\{Age_i = [70;79]\}(\gamma_{[70;79]})$		-0.151^{***}	-0.158^{***}			
		(0.007)	(0.008)			
$After_t \times \mathbf{1}\{Month_t = Mar\}(\Delta_{Mar})$				-0.144^{***}	-0.102^{***}	-0.094^{***}
				(0.004)	(0.007)	(0.008)
$After_t \times \mathbf{1}\{Month_t = Apr\}(\Delta_{Apr})$				-0.388^{***}	-0.290^{***}	-0.291^{***}
				(0.004)	(0.008)	(0.009)
$After_t \times \mathbf{1}\{Month_t = May\}(\Delta_{May})$				-0.247^{***}	-0.190^{***}	-0.192^{***}
				(0.004)	(0.008)	(0.009)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [50;59]\}(\delta_{Mar,[50;59]})$					-0.010	-0.016
					(0.009)	(0.010)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [60;69]\}(\delta_{Mar,[60;69]})$					-0.043^{***}	-0.050^{***}
					(0.009)	(0.010)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [70;79]\}(\delta_{Mar,[70;79]})$					-0.103^{***}	-0.120^{***}
					(0.009)	(0.011)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [50;59]\}(\delta_{Apr,[50;59]})$					-0.023^{*}	-0.021^{+}
					(0.010)	(0.011)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [60;69]\}(\delta_{Apr,[60;69]})$					-0.123^{***}	-0.120^{***}
					(0.010)	(0.011)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [70;79]\}(\delta_{Apr,[70;79]})$					-0.218^{***}	-0.218^{***}
					(0.010)	(0.012)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [50;59]\}(\delta_{May,[50;59]})$					-0.005	0.001
					(0.009)	(0.011)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [60;69]\}(\delta_{May,[60;69]})$					-0.074^{***}	-0.068^{***}
					(0.009)	(0.010)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [70;79]\}(\delta_{May,[70;79]})$					-0.132^{***}	-0.136^{***}
					(0.010)	(0.011)
$\mathbf{1}\{Month_t = Feb\}(\lambda_{Feb})$	-0.074^{***}	-0.074^{***}	-0.079^{***}	-0.074^{***}	-0.074^{***}	-0.079^{***}
	(0.002)	(0.002)	(0.018)	(0.002)	(0.002)	(0.018)
$\mathbf{1}\{Month_t = Mar\}(\lambda_{Mar})$	0.062^{***}	0.062^{***}	0.027	0.023^{***}	0.023^{***}	-0.006
	(0.002)	(0.002)	(0.018)	(0.003)	(0.003)	(0.018)
$\mathbf{1}\{Month_t = Apr\}(\lambda_{Apr})$	-0.044^{***}	-0.044^{***}	-0.014	-0.002	-0.002	0.018
	(0.002)	(0.002)	(0.019)	(0.003)	(0.003)	(0.019)
$\mathbf{1}\{Month_t = May\}(\lambda_{May})$	0.056^{***}	0.056^{***}	0.031^{+}	0.052^{***}	0.052^{***}	0.031^{+}
	(0.003)	(0.003)	(0.018)	(0.003)	(0.003)	(0.018)
$\mathbf{1}\{Year_t = 2019\}(\Lambda_{2019})$	0.037^{***}	0.037^{***}	0.037^{***}	0.037^{***}	0.037^{***}	0.037^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathbf{1}\{Year_t = 2020\}(\Lambda_{2020})$	0.090^{***}	0.090^{***}	0.090^{***}	0.090^{***}	0.090^{***}	0.090^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Person Fixed Effects (θ_i)	Yes	Yes	Yes	Yes	Yes	Yes
Age Group × Month FE (Ψ_{it})	No	No	Yes	No	No	Yes
Income Group × Month FE (Ψ_{it})	No	No	Yes	No	No	Yes
Observations	869,281	869,281	869,281	869,281	869,281	869,281
Adjusted R^2	0.642	0.642	0.643	0.643	0.644	0.644
Residual Std. Error	0.658	0.658	0.658	0.657	0.657	0.657

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in parenthesis. Standard errors clustered by person

Table 5: Impact of age on consumption expenditures on high- and low-contact goods and services (negative-binomial model)

	Dependent variable: $Expenses_{it}$					
	All	High Contact	Low Contact	All	High Contact	Low Contact
	(1)	(2)	(3)	(4)	(5)	(6)
$After_t$ (γ_0)	-0.174^{***}	-0.183^{***}	-0.119^{***}			
	(0.005)	(0.007)	(0.006)			
$After_t \times \mathbf{1}\{Age_i = [50;59]\}$ $(\gamma_{[50;59]})$	-0.016^{**}	-0.028^{***}	-0.024^{***}			
	(0.005)	(0.008)	(0.006)			
$After_t \times \mathbf{1}\{Age_i = [60;69]\}$ $(\gamma_{[60;69]})$	-0.073^{***}	-0.109^{***}	-0.078^{***}			
	(0.005)	(0.008)	(0.006)			
$After_t \times \mathbf{1}\{Age_i = [70;79]\}$ $(\gamma_{[70;79]})$	-0.138^{***}	-0.208^{***}	-0.108^{***}			
	(0.005)	(0.008)	(0.006)			
$After_t \times \mathbf{1}\{Month_t = Mar\}$ (Δ_{Mar})				-0.093^{***}	-0.146^{***}	-0.024^{**}
				(0.007)	(0.011)	(0.008)
$After_t \times \mathbf{1}\{Month_t = Apr\}$ (Δ_{Apr})				-0.262^{***}	-0.260^{***}	-0.192^{***}
				(0.007)	(0.011)	(0.008)
$After_t \times \mathbf{1}\{Month_t = May\}$ (Δ_{May})				-0.168^{***}	-0.142^{***}	-0.145^{***}
				(0.007)	(0.011)	(0.008)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [50;59]\}$ $(\delta_{Mar,[50;59]})$				-0.016^{+}	0.001	-0.031^{**}
				(0.009)	(0.013)	(0.010)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [60;69]\}$ $(\delta_{Mar,[60;69]})$				-0.044^{***}	-0.021^{+}	-0.084^{***}
				(0.008)	(0.012)	(0.010)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [70;79]\}$ $(\delta_{Mar,[70;79]})$				-0.104^{***}	-0.079^{***}	-0.149^{***}
				(0.009)	(0.013)	(0.010)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [50;59]\}$ $(\delta_{Apr,[50;59]})$				-0.020^{*}	-0.071^{***}	-0.017^{+}
				(0.009)	(0.013)	(0.010)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [60;69]\}$ $(\delta_{Apr,[60;69]})$				-0.105^{***}	-0.205^{***}	-0.079^{***}
				(0.008)	(0.012)	(0.010)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [70;79]\}$ $(\delta_{Apr,[70;79]})$				-0.193^{***}	-0.358^{***}	-0.092^{***}
				(0.009)	(0.013)	(0.010)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [50;59]\}$ $(\delta_{May,[50;59]})$				-0.012	-0.018	-0.025^{*}
				(0.009)	(0.013)	(0.010)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [60;69]\}$ $(\delta_{May,[60;69]})$				-0.076^{***}	-0.113^{***}	-0.071^{***}
				(0.008)	(0.012)	(0.010)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [70;79]\}$ $(\delta_{May,[70;79]})$				-0.125^{***}	-0.212^{***}	-0.080^{***}
				(0.009)	(0.013)	(0.010)
$\mathbf{1}\{Month_t = Feb\}$ (λ_{Feb})	-0.069^{***}	-0.087^{***}	-0.069^{***}	-0.069^{***}	-0.087^{***}	-0.069^{***}
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
$\mathbf{1}\{Month_t = Mar\}$ (λ_{Mar})	0.056^{***}	0.072^{***}	0.010^{***}	0.022^{***}	0.036^{***}	-0.018^{***}
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
$\mathbf{1}\{Month_t = Apr\}$ (λ_{Apr})	-0.041^{***}	-0.046^{***}	-0.036^{***}	-0.005^{+}	0.002	-0.014^{***}
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
$\mathbf{1}\{Month_t = May\}$ (λ_{May})	0.064^{***}	0.100^{***}	0.015^{***}	0.061^{***}	0.086^{***}	0.021^{***}
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
$\mathbf{1}\{Year_t = 2019\}$ (Λ_{2019})	0.025^{***}	0.029^{***}	0.023^{***}	0.025^{***}	0.028^{***}	0.023^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathbf{1}\{Year_t = 2020\}$ (Λ_{2020})	0.080^{***}	0.108^{***}	0.089^{***}	0.080^{***}	0.107^{***}	0.089^{***}
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)
Person FE (θ_i)	Yes	Yes	Yes	Yes	Yes	Yes
Deviance	930, 200	1, 039, 883	980, 300	930, 098	1, 039, 902	980, 281
Num. Obs.	869, 281	865, 846	863, 606	869, 281	865, 846	863, 606
Num. Groups (Person id)	58, 371	58, 125	57, 918	58371	58, 125	57, 918

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$
Standard errors clustered by person in parenthesis.

Table 6: Impact of age on consumption expenditures by income group (equation 1).

	Dependent variable:		
	$log(Expenses_{it})$		
	$20,061 \leq$	$]20,061;40,522]$	$\geq 40,522$
	(1)	(2)	(3)
$After_t \times \mathbf{1}\{Month_t = Mar\}$ (Δ_{Mar})	−0.054***	−0.122***	−0.141***
	(0.013)	(0.011)	(0.032)
$After_t \times \mathbf{1}\{Month_t = Apr\}$ (Δ_{Apr})	−0.230***	−0.330***	−0.374***
	(0.014)	(0.011)	(0.033)
$After_t \times \mathbf{1}\{Month_t = May\}$ (Δ_{May})	−0.148***	−0.222***	−0.241***
	(0.014)	(0.011)	(0.032)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [50;59]\}$ ($\delta_{Mar,[50;59]}$)	−0.004	−0.018	−0.009
	(0.017)	(0.013)	(0.036)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [60;69]\}$ ($\delta_{Mar,[60;69]}$)	−0.051**	−0.045**	−0.051
	(0.016)	(0.014)	(0.035)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [70;79]\}$ ($\delta_{Mar,[70;79]}$)	−0.107***	−0.153***	−0.135***
	(0.017)	(0.016)	(0.037)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [50;59]\}$ ($\delta_{Apr,[50;59]}$)	0.015	−0.029*	−0.046
	(0.018)	(0.014)	(0.039)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [60;69]\}$ ($\delta_{Apr,[60;69]}$)	−0.094***	−0.146***	−0.118**
	(0.017)	(0.015)	(0.036)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [70;79]\}$ ($\delta_{Apr,[70;79]}$)	−0.176***	−0.295***	−0.260***
	(0.018)	(0.018)	(0.039)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [50;59]\}$ ($\delta_{May,[50;59]}$)	0.032+	−0.005	−0.037
	(0.018)	(0.014)	(0.037)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [60;69]\}$ ($\delta_{May,[60;69]}$)	−0.035*	−0.089***	−0.102**
	(0.017)	(0.015)	(0.034)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [70;79]\}$ ($\delta_{May,[70;79]}$)	−0.116***	−0.162***	−0.206***
	(0.017)	(0.017)	(0.038)
$\mathbf{1}\{Year_t = 2019\}$ (Λ_{2019})	0.038***	0.038***	0.031***
	(0.003)	(0.003)	(0.006)
$\mathbf{1}\{Year_t = 2020\}$ (Λ_{2020})	0.089***	0.096***	0.068***
	(0.005)	(0.004)	(0.008)
$\mathbf{1}\{Month_t = Feb\}$ (λ_{Feb})	−0.048***	−0.081***	−0.113***
	(0.007)	(0.006)	(0.021)
$\mathbf{1}\{Month_t = Mar\}$ (λ_{Mar})	0.062***	0.016*	0.009
	(0.016)	(0.008)	(0.024)
$\mathbf{1}\{Month_t = Apr\}$ (λ_{Apr})	0.034*	−0.003	−0.016
	(0.014)	(0.009)	(0.026)
$\mathbf{1}\{Month_t = May\}$ (λ_{May})	0.081***	0.046***	0.025
	(0.012)	(0.008)	(0.023)
Person FE (θ_i)	Yes	Yes	Yes
Age Group × Month FE (Ψ_{it})	Yes	Yes	Yes
Observations	382,643	381,986	104,652
Num. Groups	25,823	25,551	6,997
Adjusted R^2	0.616	0.548	0.545
Residual Std. Error	0.688	0.627	0.642

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

Table 7: Impact of age on consumption expenditures for people with and without comorbidity

	Dependent variable:	
	$log(Expenses_{it})$	
	$Comorbidity_i = 0$	$Comorbidity_i = 1$
	(1)	(2)
$After_t \times \mathbf{1}\{Month_t = Mar\}$ (Δ_{Mar})	−0.100***	−0.125***
	(0.008)	(0.018)
$After_t \times \mathbf{1}\{Month_t = Apr\}$ (Δ_{Apr})	−0.300***	−0.374***
	(0.009)	(0.020)
$After_t \times \mathbf{1}\{Month_t = May\}$ (Δ_{May})	−0.196***	−0.204***
	(0.009)	(0.021)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [50;59]\}$ $(\delta_{Mar,[50;59]})$	−0.009	0.018
	(0.009)	(0.021)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [60;69]\}$ $(\delta_{Mar,[60;69]})$	−0.036***	0.011
	(0.009)	(0.021)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [70;79]\}$ $(\delta_{Mar,[70;79]})$	−0.083***	−0.053*
	(0.010)	(0.022)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [50;59]\}$ $(\delta_{Apr,[50;59]})$	−0.023*	0.006
	(0.010)	(0.024)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [60;69]\}$ $(\delta_{Apr,[60;69]})$	−0.114***	−0.084***
	(0.010)	(0.024)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [70;79]\}$ $(\delta_{Apr,[70;79]})$	−0.200***	−0.155***
	(0.011)	(0.025)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [50;59]\}$ $(\delta_{May,[50;59]})$	0.002	−0.010
	(0.010)	(0.024)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [60;69]\}$ $(\delta_{May,[60;69]})$	−0.058***	−0.075**
	(0.010)	(0.024)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [70;79]\}$ $(\delta_{May,[70;79]})$	−0.105***	−0.118***
	(0.011)	(0.025)
$\mathbf{1}\{Year_t = 2020\}$ (Λ_{2020})	0.056***	0.012+
	(0.003)	(0.007)
$\mathbf{1}\{Month_t = Feb\}$ (λ_{Feb})	−0.069***	−0.077***
	(0.003)	(0.006)
$\mathbf{1}\{Month_t = Mar\}$ (λ_{Mar})	0.016***	0.010
	(0.004)	(0.008)
$\mathbf{1}\{Month_t = Apr\}$ (λ_{Apr})	0.010**	0.004
	(0.004)	(0.008)
$\mathbf{1}\{Month_t = May\}$ (λ_{May})	0.051***	0.034***
	(0.004)	(0.008)
Person FE (θ_i)	Yes	Yes
Observations	493,188	85,620
Groups	49,774	8,597
Adjusted R^2	0.664	0.602
Residual Std. Error	0.649	0.597

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in parenthesis
Standard errors clustered by person

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A Appendix

This appendix is organized as follows. The first subsection presents the classification of sectors into high- and low- contact. The second subsection provides evidence of the empirical plausibility of the assumption, used in our empirical specification, that seasonal effects for January through May 2020 are the same as the common seasonal effects in 2018 and 2019. The third subsection provides results estimated by age cohort, alternative estimates to those obtained using the negative binomial specification, and results obtained using data for retirees instead of public servants. The fourth subsection provides results estimated to contrast with the economic model of consumer behavior.

A.1 Sector Classifications

Table 8: Classification of sectors into high and low contact (Part I)

code	description	class
01	Crop and animal production, hunting and related service activities	Low
02	Forestry and logging	Low
03	Fishing and aquaculture	Low
05	Mining of coal and lignite	Low
06	Extraction of crude petroleum and natural gas	Low
07	Mining of metal ores	Low
08	Other mining and quarrying	Low
09	Mining support service activities	Low
10	Manufacture of food products	Low
11	Manufacture of beverages	Low
12	Manufacture of tobacco products	Low
13	Manufacture of textiles	Low
14	Manufacture of wearing apparel	Low
15	Manufacture of leather and related products	Low
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	Low
17	Manufacture of paper and paper products	Low
18	Printing and reproduction of recorded media	Low
19	Manufacture of coke and refined petroleum products	Low
20	Manufacture of chemicals and chemical products	Low
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	Low
22	Manufacture of rubber and plastics products	Low
23	Manufacture of other non-metallic mineral products	Low
24	Manufacture of basic metals	Low
25	Manufacture of fabricated metal products, except machinery and equipment	Low
26	Manufacture of computer, electronic and optical products	Low
27	Manufacture of electrical equipment	Low
28	Manufacture of machinery and equipment n.e.c.	Low
29	Manufacture of motor vehicles, trailers and semi-trailers	Low
30	Manufacture of other transport equipment	Low
31	Manufacture of furniture	Low
32	Other manufacturing	Low
33	Repair and installation of machinery and equipment	Low
35	Electricity, gas, steam and air conditioning supply	Low
36	Water collection, treatment and supply	Low
37	Sewerage	Low
38	Waste collection, treatment and disposal activities; materials recovery	Low
39	Remediation activities and other waste management services	Low
41	Construction of buildings	Low
42	Civil engineering	Low
43	Specialized construction activities	Low
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	Medium
46	Wholesale trade, except of motor vehicles and motorcycles	High
47	Retail trade, except of motor vehicles and motorcycles	High
49	Land transport and transport via pipelines	Low

Table 9: Classification of sectors into high and low contact (Part II)

code	description	class
50	Water transport	High
51	Air transport	High
52	Warehousing and support activities for transportation	Low
53	Postal and courier activities	Low
55	Accommodation	High
56	Food and beverage service activities	High
58	Publishing activities	Low
59	Motion picture, video and television programme production, sound recording and music publishing activities	Low
60	Programming and broadcasting activities	Low
61	Telecommunications	Low
62	Computer programming, consultancy and related activities	Low
63	Information service activities	Low
64	Financial service activities, except insurance and pension funding	Low
65	Insurance, reinsurance and pension funding, except compulsory social security	Low
66	Activities auxiliary to financial service and insurance activities	Low
68	Real estate activities	Low
69	Legal and accounting activities	Low
70	Activities of head offices; management consultancy activities	Low
71	Architectural and engineering activities; technical testing and analysis	Low
72	Scientific research and development	Low
73	Advertising and market research	Low
74	Other professional, scientific and technical activities	Low
75	Veterinary activities	Low
77	Rental and leasing activities	Low
78	Employment activities	Low
79	Travel agency, tour operator, reservation service and related activities	Low
80	Security and investigation activities	Low
81	Services to buildings and landscape activities	Low
82	Office administrative, office support and other business support activities	Low
84	Public administration and defence; compulsory social security	Low
85	Education	High
86	Human health activities	High
87	Residential care activities	Medium
88	Social work activities without accommodation	Medium
90	Creative, arts and entertainment activities	High
91	Libraries, archives, museums and other cultural activities	Medium
92	Gambling and betting activities	Low
93	Sports activities and amusement and recreation activities	High
94	Activities of membership organizations	High
95	Repair of computers and personal and household goods	Low
96	Other personal service activities	Low
97	Activities of households as employers of domestic personnel	Low
98	Undifferentiated goods- and services-producing activities of private households for own use	Low
99	Activities of extraterritorial organizations and bodies	Low

A.2 Seasonality effects

Equation 1 assumes that, in the absence of the epidemic, the seasonal effects for the January through May 2020 (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 May 2020:

$$\begin{aligned} Log(Expense_{it}) = \Lambda_{2019}\mathbf{1}\{Year_t = 2019\}+ \\ \sum_{m=Feb}^{May} \lambda_m \mathbf{1}\{Month_t = m\}+ \\ \sum_{m=Feb}^{May} \phi_m \mathbf{1}\{Month_t = m\} \times \mathbf{1}\{Year_t = 2019\} + \boldsymbol{\theta_i} + \epsilon_{it} \end{aligned} \tag{3}$$

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 10 presents the regression coefficients.

Figure 11 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. For the age groups corresponding to panels (2), (3), and (4), we cannot reject the joint null hypothesis that all of the $\phi_m s$ are zero. We do reject this null hypothesis 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-19 shock. For example, in the first column of table 10 for May average log expenditures fell by 21 percent, while the value of ϕ_m for that month is -0.89 percent.

Throughout, we use logarithmic percentage changes in discussing our empirical results.

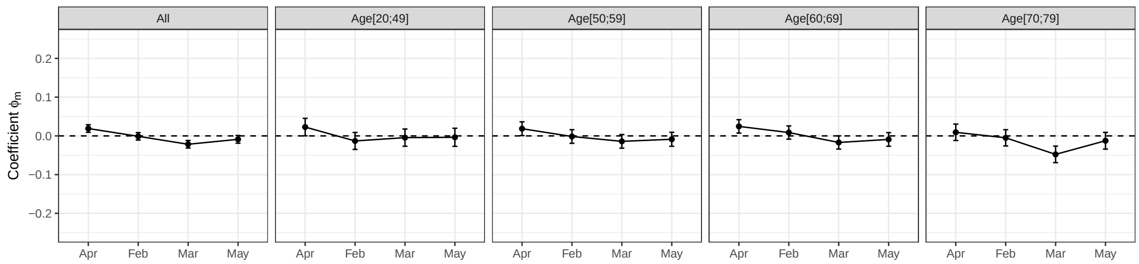

Figure 11: Seasonality effects for different age groups

A.3 Robustness of Empirical Results

In this subsection, we report the results of several robustness checks. First, we estimate separate versions of equation 1 for each age cohort. We consider versions with total expenditures (Table 11), expenditures on high- and low-contact goods (Table 12) as well as a version with co-morbidity (Table 13). This split-sample by age approach allows each cohort to have different time trends and 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-19 shock. Our results regarding age, high- and low-contact, and comorbidity are robust to the split-sample approach.

Second, we provide estimates for how different age groups changed their overall consumption expenditures and spending on high-contact and low-contact sectors of the economy using an alternative to the negative binomial specification. This alternative is the Poisson pseudo-maximum likelihood estimation with fixed effects proposed by Silva and Tenreyro (2011). We report the results in Table 14 which are consistent with those obtained using the negative binomial specification.

Third, 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 15 is the analogue of Table 4. 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 10: Trends and seasonal effects in 2018 and 2019

	Dependent variable:				
	$log(Expenses_{it})$				
	All	[20;49]	[50;59]	[60;69]	[70;79]
	(1)	(2)	(3)	(4)	(5)
$\mathbf{1}\{Year_t = 2019\}$ (Λ_{2019})	0.041***	0.064***	0.051***	0.033***	0.026**
	(0.004)	(0.009)	(0.007)	(0.007)	(0.008)
Feb (λ_{Feb})	−0.080***	−0.078***	−0.075***	−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**	0.048***
	(0.004)	(0.008)	(0.007)	(0.006)	(0.008)
Apr (λ_{Apr})	−0.013***	−0.006	−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)
$\mathbf{1}\{Year_t = 2019\}$ × 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***	0.023*	0.019*	0.025**	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)
Constant	5.893***	6.086***	6.010***	5.875***	5.654***
	(0.005)	(0.010)	(0.008)	(0.008)	(0.010)
χ^2 ($\phi_{Feb} = 0$, $\phi_{Mar} = 0$, $\phi_{Apr} = 0$, $\phi_{May} = 0$)	21.448	4.045	4.569	7.779	9.834
P-value	0.0003	0.400	0.334	0.100	0.043
Observations	580,576	99,591	152,596	186,674	141,715
R^2	0.002	0.004	0.003	0.002	0.001
Residual Std. Error	1.091	0.948	1.015	1.118	1.175

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in parenthesis
Standard errors clustered by person

Table 11: Changes in expenditures by age group

	Dependent variable:							
	$log(Expenses_{it})$							
	[20;49]	[50;59]	[60;69]	[70;79]	[20;49]	[50;59]	[60;69]	[70;79]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$After_t$	−0.226***	−0.237***	−0.263***	−0.303***				
	(0.007)	(0.005)	(0.005)	(0.006)				
$After_t \times \mathbf{1}\{Month_t = Mar\}$					−0.127***	−0.142***	−0.136***	−0.167***
					(0.009)	(0.007)	(0.006)	(0.008)
$After_t \times \mathbf{1}\{Month_t = Apr\}$					−0.324***	−0.345***	−0.403***	−0.462***
					(0.009)	(0.007)	(0.007)	(0.009)
$After_t \times \mathbf{1}\{Month_t = May\}$					−0.225***	−0.223***	−0.251***	−0.281***
					(0.009)	(0.007)	(0.007)	(0.008)
$\mathbf{1}\{Year_t = 2019\}$	0.065***	0.050***	0.032***	0.011*	0.065***	0.050***	0.032***	0.011*
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
$\mathbf{1}\{Year_t = 2020\}$	0.136***	0.128***	0.079***	0.029***	0.136***	0.128***	0.079***	0.029***
	(0.007)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)
$\mathbf{1}\{Month_t = Feb\}$	−0.077***	−0.069***	−0.081***	−0.070***	−0.077***	−0.069***	−0.081***	−0.070***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
$\mathbf{1}\{Month_t = Mar\}$	0.056***	0.064***	0.058***	0.069***	0.024***	0.032***	0.015***	0.024***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
$\mathbf{1}\{Month_t = Apr\}$	−0.024***	−0.026***	−0.057***	−0.061***	0.009	0.010*	−0.010*	−0.009
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
$\mathbf{1}\{Month_t = May\}$	0.063***	0.064***	0.045***	0.057***	0.062***	0.060***	0.041***	0.050***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	149,319	228,711	279,481	211,770	149,319	228,711	279,481	211,770
R^2	0.598	0.659	0.669	0.671	0.599	0.659	0.671	0.672
Residual Std. Error	0.629	0.616	0.669	0.705	0.628	0.615	0.668	0.704

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in parenthesis. Standard errors clustered by person

Table 12: Changes in expenditures on high- and low- contact goods and services by age group (negative-binomal model).

	Dependent variable:							
	$Expenses_{it}$							
	High Contact				Low Contact			
	[20;49]	[50;59]	[60;69]	[70;79]	[20;49]	[50;59]	[60;69]	[70;79]
$After_t$	−0.201***	−0.231***	−0.293***	−0.356***	−0.170***	−0.176***	−0.169***	−0.191***
	(0.010)	(0.008)	(0.008)	(0.010)	(0.008)	(0.006)	(0.006)	(0.007)
$\mathbf{1}\{Year_t = 2019\}$	0.057***	0.037***	0.033***	−0.007	0.043***	0.041***	0.016***	−0.001
	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)
$\mathbf{1}\{Year_t = 2020\}$	0.141***	0.134***	0.111***	0.049***	0.146***	0.135***	0.059***	0.036***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.005)	(0.005)	(0.006)
$\mathbf{1}\{Month_t = Feb\}$	−0.106***	−0.078***	−0.091***	−0.078***	−0.046***	−0.061***	−0.088***	−0.070***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.004)	(0.005)
$\mathbf{1}\{Month_t = Mar\}$	0.034***	0.068***	0.079***	0.095***	0.053***	0.023***	−0.010*	−0.008
	(0.008)	(0.007)	(0.006)	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)
$\mathbf{1}\{Month_t = Apr\}$	−0.017*	−0.027***	−0.053***	−0.079***	−0.003	−0.024***	−0.062***	−0.036***
	(0.008)	(0.007)	(0.006)	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)
$\mathbf{1}\{Month_t = May\}$	0.104***	0.109***	0.097***	0.093***	0.044***	0.020***	−0.009	0.023***
	(0.008)	(0.007)	(0.006)	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deviance	177, 522.758	272, 415.484	334, 514.108	254, 653.934	167, 402.887	257, 453.803	314, 869.696	239, 930.900
Num. Obs.	149, 075	227, 877	278, 225	210, 669	149, 140	228, 043	277, 835	208, 588
Num. Groups (Person id)	9, 962	15, 242	18, 669	14, 252	9, 964	15, 249	18, 626	14, 079

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
Cluster robust standard errors in parenthesis. Standard errors clustered by person

Table 13: Impact of comorbidity on expenditures by age group

	Dependent variable:							
	$log(Expenses_{it})$							
	[20;49]	[50;59]	[60;69]	[70;79]	[20;49]	[50;59]	[60;69]	[70;79]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$After_t$	−0.222***	−0.229***	−0.254***	−0.287***				
	(0.008)	(0.006)	(0.006)	(0.008)				
$After_t \times Comorbidity$	−0.071***	−0.056***	−0.051***	−0.050***				
	(0.015)	(0.011)	(0.011)	(0.013)				
$After_t \times \mathbf{1}\{Month_t = Mar\}$					−0.121***	−0.132***	−0.125***	−0.141***
					(0.010)	(0.008)	(0.008)	(0.009)
$After_t \times \mathbf{1}\{Month_t = Apr\}$					−0.324***	−0.344***	−0.403***	−0.456***
					(0.011)	(0.009)	(0.009)	(0.010)
$After_t \times \mathbf{1}\{Month_t = May\}$					−0.221***	−0.211***	−0.234***	−0.265***
					(0.011)	(0.008)	(0.008)	(0.010)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times Comorbidity$					−0.056**	−0.029*	−0.010	−0.027+
					(0.018)	(0.014)	(0.014)	(0.016)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times Comorbidity$					−0.106***	−0.077***	−0.076***	−0.061**
					(0.020)	(0.016)	(0.016)	(0.019)
$After_t \times \mathbf{1}\{Month_t = May\} \times Comorbidity$					−0.050*	−0.063***	−0.068***	−0.063***
					(0.021)	(0.016)	(0.015)	(0.017)
$\mathbf{1}\{Month_t = Feb\}$	−0.075***	−0.065***	−0.073***	−0.070***	−0.075***	−0.065***	−0.072***	−0.070***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
$\mathbf{1}\{Month_t = Mar\}$	0.078***	0.078***	0.076***	0.076***	0.027***	0.028***	0.009	0.002
	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)
$\mathbf{1}\{Month_t = Apr\}$	−0.029***	−0.038***	−0.073***	−0.090***	0.024**	0.021***	0.003	−0.006
	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)
$\mathbf{1}\{Month_t = May\}$	0.068***	0.066***	0.045***	0.053***	0.066***	0.057***	0.036***	0.043***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)
$\mathbf{1}\{Year_t = 2020\}$	0.076***	0.078***	0.042***	0.008	0.076***	0.078***	0.042***	0.009
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,530	152,415	186,088	140,775	99,530	152,415	186,088	140,775
R^2	0.629	0.683	0.696	0.707	0.630	0.684	0.697	0.709
Residual Std. Error	0.618	0.604	0.656	0.682	0.617	0.603	0.654	0.680

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in parenthesis. Standard errors clustered by person

Table 14: Impact of age on expenditure on high- and low- contact goods and services (Poisson model)

	$Expenses_{it}$					
	All Poisson	High Contact Poisson	Low Contact Poisson	All Poisson	High Contact Poisson	Low Contact Poisson
$After_t$ (γ_0)	-0.178^{***}	-0.167^{***}	-0.101^{***}			
	(0.000)	(0.000)	(0.000)			
$After_t \times \mathbf{1}\{Age_i = [50;59]\}$ ($\gamma_{[50;59]}$)	-0.055^{***}	-0.050^{***}	-0.057^{***}			
	(0.000)	(0.000)	(0.000)			
$After_t \times \mathbf{1}\{Age_i = [60;69]\}$ ($\gamma_{[60;69]}$)	-0.104^{***}	-0.140^{***}	-0.104^{***}			
	(0.000)	(0.000)	(0.000)			
$After_t \times \mathbf{1}\{Age_i = [70;79]\}$ ($\gamma_{[70;79]}$)	-0.159^{***}	-0.231^{***}	-0.138^{***}			
	(0.000)	(0.001)	(0.001)			
$After_t \times \mathbf{1}\{Month_t = Mar\}$ (Δ_{Mar})				-0.040^{***}	-0.139^{***}	0.075^{***}
				(0.000)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = Apr\}$ (Δ_{Apr})				-0.299^{***}	-0.233^{***}	-0.215^{***}
				(0.000)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = May\}$ (Δ_{May})				-0.215^{***}	-0.136^{***}	-0.185^{***}
				(0.000)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [50;59]\}$ ($\delta_{Mar,[50;59]}$)				-0.096^{***}	-0.014^{***}	-0.123^{***}
				(0.000)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [60;69]\}$ ($\delta_{Mar,[60;69]}$)				-0.116^{***}	-0.054^{***}	-0.168^{***}
				(0.000)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age_i = [70;79]\}$ ($\delta_{Mar,[70;79]}$)				-0.187^{***}	-0.106^{***}	-0.255^{***}
				(0.001)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [50;59]\}$ ($\delta_{Apr,[50;59]}$)				-0.035^{***}	-0.099^{***}	0.007^{***}
				(0.001)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [60;69]\}$ ($\delta_{Apr,[60;69]}$)				-0.106^{***}	-0.246^{***}	-0.054^{***}
				(0.001)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age_i = [70;79]\}$ ($\delta_{Apr,[70;79]}$)				-0.224^{***}	-0.406^{***}	-0.128^{***}
				(0.001)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [50;59]\}$ ($\delta_{May,[50;59]}$)				-0.029^{***}	-0.044^{***}	-0.038^{***}
				(0.001)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [60;69]\}$ ($\delta_{May,[60;69]}$)				-0.088^{***}	-0.143^{***}	-0.074^{***}
				(0.001)	(0.001)	(0.001)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age_i = [70;79]\}$ ($\delta_{May,[70;79]}$)				-0.078^{***}	-0.225^{***}	-0.018^{***}
				(0.001)	(0.001)	(0.001)
$\mathbf{1}\{Month_t = Feb\}$ (λ_{Feb})	-0.065^{***}	-0.068^{***}	-0.054^{***}	-0.065^{***}	-0.068^{***}	-0.054^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\mathbf{1}\{Month_t = Mar\}$ (λ_{Mar})	0.068^{***}	0.080^{***}	0.048^{***}	0.033^{***}	0.052^{***}	0.010^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\mathbf{1}\{Month_t = Apr\}$ (λ_{Apr})	-0.033^{***}	-0.028^{***}	-0.013^{***}	0.002^{***}	0.012^{***}	0.010^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\mathbf{1}\{Month_t = May\}$ (λ_{May})	0.078^{***}	0.094^{***}	0.047^{***}	0.081^{***}	0.084^{***}	0.061^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\mathbf{1}\{Year_t = 2019\}$ (Λ_{2019})	0.028^{***}	0.039^{***}	0.034^{***}	0.028^{***}	0.039^{***}	0.034^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\mathbf{1}\{Year_t = 2020\}$ (Λ_{2020})	0.072^{***}	0.096^{***}	0.077^{***}	0.072^{***}	0.096^{***}	0.077^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Person FE (θ_i)	Yes	Yes	Yes	Yes	Yes	Yes
Num. Obs.	869281	865846	863606	869281	865846	863606
Num. Groups (Person id)	58371	58125	57918	58371	58125	57918

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$
Cluster robust standard errors in parenthesis. Standard errors clustered by person

Table 15: Impact of age on consumption expenditures for retirees

	Dependent variable:					
	$log(Expense_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$After_t$ (γ_0)	−0.211***	−0.108***	−0.095***			
	(0.003)	(0.023)	(0.026)			
$After_t \times \mathbf{1}\{AgeGroup_i = [50;59]\}$ ($\gamma_{[50;59]}$)		−0.018	−0.010			
		(0.026)	(0.029)			
$After_t \times \mathbf{1}\{AgeGroup_i = [60;69]\}$ ($\gamma_{[60;69]}$)		−0.071**	−0.085**			
		(0.024)	(0.027)			
$After_t \times \mathbf{1}\{AgeGroup_i = [70;79]\}$ ($\gamma_{[70;79]}$)		−0.122***	−0.137***			
		(0.024)	(0.026)			
$After_t \times \mathbf{1}\{Month_t = Mar\}$ (Δ_{Mar})				−0.097***	−0.008	0.004
				(0.003)	(0.031)	(0.037)
$After_t \times \mathbf{1}\{Month_t = Apr\}$ (Δ_{Apr})				−0.329***	−0.191***	−0.176***
				(0.004)	(0.037)	(0.040)
$After_t \times \mathbf{1}\{Month_t = May\}$ (Δ_{May})				−0.209***	−0.127***	−0.114**
				(0.003)	(0.032)	(0.037)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{AgeGroup_i = [50;59]\}$ ($\delta_{Mar,[50;59]}$)					−0.028	−0.018
					(0.035)	(0.042)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{AgeGroup_i = [60;69]\}$ ($\delta_{Mar,[60;69]}$)					−0.059+	−0.071+
					(0.032)	(0.038)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{AgeGroup_i = [70;79]\}$ ($\delta_{Mar,[70;79]}$)					−0.106***	−0.119**
					(0.032)	(0.038)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{AgeGroup_i = [50;59]\}$ ($\delta_{Apr,[50;59]}$)					−0.012	−0.006
					(0.041)	(0.044)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{AgeGroup_i = [60;69]\}$ ($\delta_{Apr,[60;69]}$)					−0.103**	−0.117**
					(0.037)	(0.040)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{AgeGroup_i = [70;79]\}$ ($\delta_{Apr,[70;79]}$)					−0.161***	−0.178***
					(0.037)	(0.040)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{AgeGroup_i = [50;59]\}$ ($\delta_{May,[50;59]}$)					−0.012	−0.006
					(0.036)	(0.041)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{AgeGroup_i = [60;69]\}$ ($\delta_{May,[60;69]}$)					−0.051	−0.068+
					(0.032)	(0.037)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{AgeGroup_i = [70;79]\}$ ($\delta_{May,[70;79]}$)					−0.100**	−0.113**
					(0.032)	(0.037)
$\mathbf{1}\{Month_t = Feb\}$ (λ_{Apr})	−0.064***	−0.064***	−0.086***	−0.064***	−0.064***	−0.086***
	(0.002)	(0.002)	(0.026)	(0.002)	(0.002)	(0.026)
$\mathbf{1}\{Month_t = Mar\}$ (λ_{Mar})	0.041***	0.041***	−0.001	0.003	0.003	−0.033
	(0.002)	(0.002)	(0.027)	(0.002)	(0.002)	(0.028)
$\mathbf{1}\{Month_t = Apr\}$ (λ_{Apr})	−0.051***	−0.051***	−0.075**	−0.012***	−0.012***	−0.049+
	(0.002)	(0.002)	(0.027)	(0.002)	(0.002)	(0.027)
$\mathbf{1}\{Month_t = May\}$ (λ_{May})	0.033***	0.033***	−0.012	0.033***	0.033***	−0.006
	(0.002)	(0.002)	(0.027)	(0.002)	(0.002)	(0.029)
$\mathbf{1}\{Year_t = 2019\}$ (Λ_{2019})	0.022***	0.022***	0.022***	0.022***	0.022***	0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathbf{1}\{Year_t = 2020\}$ (Λ_{2020})	0.054***	0.054***	0.054***	0.054***	0.054***	0.054***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Person Fixed Effects (θ_i)	Yes	Yes	Yes	Yes	Yes	Yes
Age Group × Month FE (Ψ_{it})	No	No	Yes	No	No	Yes
Income Group × Month FE (Ψ_{it})	No	No	Yes	No	No	Yes
Observations	1,347,407	1,347,407	1,347,407	1,347,407	1,347,407	1,347,407
Adjusted R^2	0.698	0.698	0.698	0.698	0.698	0.698
Residual Std. Error	0.748	0.748	0.747	0.747	0.747	0.747

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

Cluster robust standard errors in parenthesis. Standard errors clustered by person

A.4 Model Calibration

Table 16: Impact of age on consumption expenditures for consumers older and younger than 60 (used in economic model calibration)

	Dependent variable:					
	$log(Expense_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$After_t(\gamma_0)$	-0.259^{***}	-0.201^{***}	-0.200^{***}			
	(0.003)	(0.004)	(0.004)			
$After_t \times \mathbf{1}\{Age \geq 60\}(\gamma_{\geq 60})$		-0.103^{***}	-0.106^{***}			
		(0.005)	(0.005)			
$After_t \times \mathbf{1}\{Month_t = Mar\}(\Delta_{Mar})$				-0.144^{***}	-0.108^{***}	-0.104^{***}
				(0.004)	(0.005)	(0.005)
$After_t \times \mathbf{1}\{Month_t = Apr\}(\Delta_{Apr})$				-0.388^{***}	-0.304^{***}	-0.304^{***}
				(0.004)	(0.005)	(0.006)
$After_t \times \mathbf{1}\{Month_t = May\}(\Delta_{May})$				-0.247^{***}	-0.193^{***}	-0.191^{***}
				(0.004)	(0.005)	(0.005)
$After_t \times \mathbf{1}\{Month_t = Mar\} \times \mathbf{1}\{Age \geq 60\}(\delta_{Mar,\geq 60})$					-0.062^{***}	-0.071^{***}
					(0.006)	(0.007)
$After_t \times \mathbf{1}\{Month_t = Apr\} \times \mathbf{1}\{Age \geq 60\}(\delta_{Apr,\geq 60})$					-0.150^{***}	-0.149^{***}
					(0.007)	(0.007)
$After_t \times \mathbf{1}\{Month_t = May\} \times \mathbf{1}\{Age \geq 60\}(\delta_{May,\geq 60})$					-0.096^{***}	-0.098^{***}
					(0.006)	(0.007)
$\mathbf{1}\{Month_t = Feb\}(\lambda_{Feb})$	-0.074^{***}	-0.074^{***}	-0.072^{***}	-0.074^{***}	-0.074^{***}	-0.072^{***}
	(0.002)	(0.002)	(0.018)	(0.002)	(0.002)	(0.018)
$\mathbf{1}\{Month_t = Mar\}(\lambda_{Mar})$	0.062^{***}	0.062^{***}	0.032^{+}	0.023^{***}	0.023^{***}	0.0004
	(0.002)	(0.002)	(0.017)	(0.003)	(0.003)	(0.017)
$\mathbf{1}\{Month_t = Apr\}(\lambda_{Apr})$	-0.044^{***}	-0.044^{***}	-0.016	-0.002	-0.002	0.018
	(0.002)	(0.002)	(0.018)	(0.003)	(0.003)	(0.018)
$\mathbf{1}\{Month_t = May\}(\lambda_{May})$	0.056^{***}	0.056^{***}	0.034^{+}	0.052^{***}	0.052^{***}	0.031^{+}
	(0.003)	(0.003)	(0.018)	(0.003)	(0.003)	(0.018)
$\mathbf{1}\{Year_t = 2019\}(\Lambda_{2019})$	0.037^{***}	0.037^{***}	0.037^{***}	0.037^{***}	0.037^{***}	0.037^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathbf{1}\{Year_t = 2020\}(\Lambda_{2020})$	0.090^{***}	0.090^{***}	0.090^{***}	0.090^{***}	0.090^{***}	0.090^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Individual FE (θ_i)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE (Λ_y)	Yes	Yes	Yes	Yes	Yes	Yes
Month FE (λ_y)	Yes	Yes	Yes	Yes	Yes	Yes
Age Group x Month FE (Ψ_{it})	No	No	Yes	No	No	Yes
Income Group x Month FE (Ψ_{it})	No	No	Yes	No	No	Yes
Observations	869,281	869,281	869,281	869,281	869,281	869,281
Adjusted R^2	0.642	0.642	0.643	0.643	0.644	0.644
Residual Std. Error	0.658	0.658	0.658	0.657	0.657	0.657

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in parenthesis
Standard errors clustered by person