DISCUSSION PAPER SERIES

DP15525

THE COVID-19 CRISIS AND CONSUMPTION: SURVEY EVIDENCE FROM SIX EU COUNTRIES

Dimitris Christelis, Dimitris Georgarakos, Tullio Jappelli and Geoff Kenny

MACROECONOMICS AND GROWTH

ISSN 0265-8003

THE COVID-19 CRISIS AND CONSUMPTION: SURVEY EVIDENCE FROM SIX EU COUNTRIES

Dimitris Christelis, Dimitris Georgarakos, Tullio Jappelli and Geoff Kenny

Discussion Paper DP15525
Published 07 December 2020
Submitted 07 December 2020

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

THE COVID-19 CRISIS AND CONSUMPTION: SURVEY EVIDENCE FROM SIX EU COUNTRIES

Abstract

Using new panel data from a representative survey of households in the six largest euro area economies, the paper estimates the impact of the Covid-19 crisis on consumption. The panel provides, each month, household-specific indicators of the concern about finances due to Covid-19 from the first peak of the pandemic until October 2020. The results show that this concern causes a significant reduction in non-durable consumption. The paper also explores the potential impact on consumption of government interventions and of another wave of Covid-19, using household-level consumption adjustments to scenarios that involve positive and negative income shocks. Fears of the financial consequences of the pandemic induce a significant reduction in the marginal propensity to consume, an effect consistent with models of precautionary saving and liquidity constraints. The results are robust to endogeneity concerns through use of panel fixed effects and partial identification methods, which account also for time-varying unobservable variables, and provide informative identification regions of the average treatment effect of the concern for Covid-19 under weak assumptions.

JEL Classification: D12, D81, E21, G51, H31

Keywords: Consumption, Income Shocks, marginal propensity to consume, Financial concerns, fiscal policies

Dimitris Christelis - dimitris.christelis@gmail.com
University of Naples Federico II, CSEF, CFS and CEPAR

Dimitris Georgarakos - dimitris.georgarakos@ecb.europa.eu
European Central Bank

Tullio Jappelli - tullio.jappelli@unina.it
University of Naples Federico II and CEPR

Geoff Kenny - geoff.kenny@ecb.europa.eu
European Central Bank

1. Introduction

All major economies are currently facing two-digit drops in GDP due to the ongoing Covid-19 outbreak, and governments are responding to this unprecedented shock with a variety of interventions. According to the aggregate data for the largest euro area economies, household spending dropped by more than 10% on average in the second quarter of 2020 compared to the second quarter in 2019. At the same time, households are exposed to a multifaceted shock that affects them to a different degree, depending on an array of characteristics, such as job arrangements, household composition, access to liquidity, personal health conditions, and region of residence. Against this background, the present paper provides direct evidence on household consumption adjustments in response to the first peak of the pandemic and its immediate aftermath in the euro area and attempts to estimate how much of the consumption drop has been due to households' concern about the financial consequences of Covid-19. The paper also provides evidence on possible consumption adjustments in response to positive and negative income shocks that households could experience due, for example, to government support measures or to another Covid-19 wave.

The paper uses novel panel data from the Consumer Expectations Survey (CES), an ongoing survey administered by the ECB that interviews, since April 2020, about 10,000 households in the six largest euro area economies (Germany, France, Italy, Spain, Netherlands and Belgium) on a monthly frequency. The survey is representative of the underlying populations and collects via the internet high-frequency and fully harmonized information on demographics, income, consumption and several expectation variables. In particular, the survey asks questions on the way that households perceive the economic consequences of the pandemic, data on realized consumption, and questions using income shock scenarios to elicit every households' propensity to spend or save. Not all information is available every month, but for many variables (including perceptions of the financial consequences of Covid-19 and consumption) we are able to exploit the panel nature of the survey from April to October 2020.

The paper makes two contributions to the literature. First, it offers new evidence on the consumption response to the Covid-19 outbreak in six Euro area countries. The empirical strategy exploits household information on the perceived severity of the financial consequences due to the Covid-19 shock. That is, it provides direct evidence on a household-specific channel through which the pandemic impacts household consumption, by examining whether people who are more concerned about the financial consequences of the pandemic are those who decrease consumption more. The paper identifies the effect of interest via different estimation techniques, such as panel fixed effects and partial identification (PI) methods that explicitly account for both time-invariant and time-varying unobserved factors that can lead to treatment selection.

The paper estimates a strong effect of financial concerns due to Covid-19 on spending on non-durables. Given that estimation controls for current income, socio-economic variables, household unobserved heterogeneity and aggregate effects, precautionary saving is a natural explanation for the negative association between concerns for the financial consequences of Covid-19 and consumption. Moreover, the paper finds that the effects of Covid-19 outbreak on consumption mainly operate through households' perceptions about the financial repercussions of the shock and not via their concerns about the effects of the pandemic on their own health per se.

A second contribution of the paper is to explore the future possible consequences of government interventions to mitigate the impact of the pandemic through an income transfer as well as the likely consumption impact of a Covid-19 second or third wave through the associated income loss. To this end, the survey elicits household-specific estimates of the marginal propensity to consume non-durable goods (MPC) and of the marginal propensity to spend on both non-durables and durables (MPS) in response to positive and negative income shock scenarios. Using these direct measures, the paper can then explore the direct implications of financial concerns due to Covid-19 for both the MPC and MPS. As reviewed in the next section, we therefore build on recent literature that studies consumption behavior using direct survey evidence. As in previous studies, we explore MPC and MPS heterogeneity in household resources and demographic characteristics, but the focus of the paper is on the relation between financial concerns due to Covid-19 and MPC and MPS from positive and negative income shocks. We find that, controlling for household resources and demographic characteristics, financial concerns due to Covid-19 amplify the negative consumption effect of a negative income shock. On the other hand, pandemic-induced financial concerns tend to attenuate the consumption adjustment due to a positive income shock. We also show that such financial concerns are not distributed evenly across the population, but are more pronounced among younger, liquidity constrained households and the unemployed. Taken together, our findings suggest that targeted government interventions that aim to lessen the financial concerns of the more vulnerable groups will support consumption of these group and will make future support measures more effective.

The paper is organized as follows. Section 2 summarizes previous studies on the dynamics of consumption during the first wave of Covid-19 and the literature on direct survey evidence about intentions to spend from positive or negative income shocks. Section 3 describes the CES panel, and Section 4 the question on concern for Covid-19 as well as the income shock scenarios that allow deducing household-specific MPCs. Section 5, using data from April to October 2020, presents evidence on the relation between the concern for the households' financial situation due to Covid-19 and realized consumption, as well as the MPC from positive and negative income changes. Section 6 presents PI estimates to identify parameter regions of the effect of the financial concern due to Covid-19 on observed consumption and the MPCs while relying on weak identification assumptions. Section 7 summarizes our findings and discusses policy implications.

2. Related literature

A growing number of studies investigate the consumption effect of the pandemic in the US, and, to a lesser extent, in Europe mainly due to the lack of high-frequency, cross-country comparable household surveys that provide very timely data. The extant Covid-19 related literature refers to individual countries and relies mostly on administrative data. The studies are mainly concerned with the timing of the consumption response during the pandemic, and the heterogeneity of the response of different expenditure categories. They typically identify the effect of interest by using area-level measures of Covid-19 impact (e.g., deaths per region). Notably, they do not rely on a household-specific measure of exposure to Covid-19 shock that factors in household heterogeneity and allows studying the transmission of the shock to household consumption.

Baker et al. (2020) use transaction-level data for the U.S. and find that in March, at the start of the pandemic, spending increased sharply, particularly in retail, credit card spending and food items. This was followed by a sharp decrease in overall spending in

April. Cox et al. (2020) suggest that U.S. spending declines in the initial months of the recession were primarily caused by direct effects of the pandemic, rather than resulting from labor market disruptions. Chetty et al. (2020) focus on fiscal policy interventions. They track economic activity in the U.S. at a granular level using anonymized data from private companies, analyze heterogeneity in the impacts of the pandemic across geographic areas and income groups, and use event study designs to estimate the causal effects of fiscal policies aimed at mitigating the adverse impacts of Covid-19.

Outside the U.S., Chronopoulos et al. (2020) find that consumer spending in the U.K. was relatively stable in the early stages of the pandemic, while later spending declined quite significantly. Hacioglu et al. (2020) and Dunn et al. (2020), also using U.K. data, find large effects of the pandemic on specific sectors, such as accommodations, restaurants and transportation, offset by large increase in food and beverage store sales. Andersen et al. (2020) use bank account transaction data from Denmark showing that total card spending was reduced by 25% during the early phase of the crisis. Bounie et al. (2020) provide evidence of the consumption response in France, and Carvalho et al. (2020a, 2020b) in Portugal and Spain. We build on this literature by providing new evidence for the euro area and by identifying a household-specific channel through which the pandemic affects consumption.

The paper connects also to research eliciting the MPC (or the MPS, depending on studies) using direct survey questions. This approach was pioneered by Shapiro and Slemrod (1995; 2009), who report evidence on the consumption response to income changes induced by tax stimulus programs. A complementary approach is to use survey questions asking respondents to report their MPC in response to a positive transitory income shock (Jappelli and Pistaferri, 2014). Recent papers utilize scenarios that involve both positive and negative income shocks that also vary by size (Christelis et al., 2019, henceforth CGJPR; Fuster et al., 2017; Bunn et al., 2018; Jappelli and Pistaferri, 2020). The main advantage of this approach is that it allows comparing the consumption response of the *same household* to shocks of different sign. Findings from these recent studies confirm the theoretical prediction of models with liquidity constraints and precautionary saving, namely that the MPC for negative shocks is larger than the MPC from positive shocks.

The evidence regarding the relation between MPC and household resources is more mixed, however. Bunn et al. (2018), Fuster et al. (2017) and CGJPR find that the MPC with respect to windfall losses declines with cash on hand but find little to no relation between MPC with respect to windfall gains and household resources. Instead, Jappelli and Pistaferri (2020) find a negative relation between the MPC and cash on hand also for positive income shocks. We expand this literature by reporting the various MPC's for positive and negative income shocks for six eurozone countries, relating them to household resources, and focusing on the link between concern for Covid-19 and reported intentions to spend.

3. The CES

For our analysis, we use the ECB's Consumer Expectations Survey (CES) - a new online high frequency panel survey of euro area consumer expectations and behavior. Building on recent international experiences and advances in survey methodology and design, e.g., as reflected, for example, in the Federal Reserve Bank of New York's Survey of Consumer Expectations (Armantier et al., 2016), the CES was launched in pilot phase in January 2020. The CES has several important and innovative features that help facilitate rich analysis of economic shocks and their transmission via the household sector. Below we provide a brief summary of these main features – see Georgarakos and Kenny (2020) for a more detailed description of the CES, and ECB (2020) for a first evaluation of the survey.

The CES currently covers the six largest euro area economies (Belgium, Germany, Italy, France, Spain, and the Netherlands) and has achieved its target sample size of approximately 10,000 households since April 2020. In this paper we use seven months of data, covering the entire pandemic crisis (from April to October 2020). The sample is comprised of anonymized individual-level responses from approximately 2,000 survey participants from each of the four largest euro area countries (Germany, Italy, France, Spain) and 1,000 in each of the two smaller countries (Belgium, the Netherlands). Three out of four participants in the four largest euro area countries are recruited via random dialing while the remaining are drawn from existing samples. The survey provides sample weights that we use to make statistics population-representative.

The large sample size helps ensure the survey's overall representativeness of population structures at both the euro area and component country levels. Respondents are invited to answer online questionnaires every month and must leave the panel between 12 and 18 months after joining. Each respondent completes a background questionnaire upon entry into the panel. This provides a range of important background information that hardly changes on a monthly frequency (e.g. family situation, household annual income, accumulated wealth). More time-sensitive information is collected in a series of monthly, quarterly and ad hoc topical questionnaires. For example, expectations and uncertainty measures for both individual future outcomes (e.g. household income growth, access to credit) and macroeconomic concepts (e.g. inflation, growth and unemployment) as well as concerns about the effect of the Covid-19 shock on own finances are asked every month. Detailed questions about household consumption expenditures are asked every quarter, while questions on consumption adjustments to different income shock scenarios are asked in ad hoc topical modules.

The survey's online nature is particularly important in allowing the questionnaires' respond to evolving economic developments. For example, as described further below, it was possible to introduce the new topical and targeted questions linked to the impact of Covid-19 on households almost immediately following the onset of the pandemic. Last, the CES is an incentivized survey with respondents receiving a gratuity with a relatively modest monetary value in recognition for their participation. These incentives signal the important value of the data supplied by respondents and strengthen the CES's overall quality by promoting high overall survey response rates, strong panel retention and minimal skipping by participants of individual questions.

4. Descriptive analysis

In every month, from April to October 2020, the CES asks respondents directly about their concerns about the impact of the Covid-19 shock on the financial situation of their household. In addition, in April, July and October the survey collects information about monthly non-durable consumption. In May, the survey asks about the consumption response to two transitory income shock scenarios (both positive and negative). In June the question on a positive income shock is repeated, but not the question on the negative shock. In this section we report information and descriptive statistics of these variables, and their associations with consumption, providing the main ingredients for the econometric analysis.

4.1. Concern for the household's financial situation due to Covid-19

The survey asks respondents the following question on the economic impact of the pandemic:

> *How concerned are you about the impact of the coronavirus (COVID-19) on the financial situation of your household (coded from 0, not concerned, to 10, extremely concerned).*

This variable allows us to gauge the idiosyncratic financial concerns due to Covid-19 for each household, to compare them across demographic groups and countries, and to associate such concerns with consumption adjustments during the pandemic. Importantly, the variable refers to concern for the "financial situation of the household", not generic concern. As we shall see, a different variable considers concern for the impact of the coronavirus for the health of the respondent and his or her family.

As shown in Table 1, the sample mean of this variable is 6.08, with a standard deviation of 2.7. The other statistics of Table 1 show some of the characteristics of the sample in terms of age, education, gender, and family size. Income refers to disposable income of the household in the 12 months preceding the interview and is PPP adjusted. Information on consumption is collected in April, July and October 2020 (i.e. on a quarterly basis) and regards spending on twelve subcategories of non-durable goods.[1] We use data that span the months from April to October 2020 (i.e. capturing the first peak of the pandemic and its immediate aftermath), although as mentioned not all variables are available every month.

Figure 1 plots the histograms of household financial concerns due to Covid-19 by country. The figure reveals considerable heterogeneity, both within and across countries. The histograms are more skewed to the right in those countries that in Spring 2020

[1] The CES asks to report household spending in the last month on goods and services in the following categories: food, beverages, groceries, tobacco; restaurants, cafes, canteens; housing (incl. rent); utilities; furnishing, housing equipment, small appliances and routine maintenance of the house; clothing, footwear; health; transport; travel, recreation, entertainment and culture; education; debt repayments; and other. Total non-durable consumption consists of the total amount spent on these categories excluding debt repayments. The survey design for consumption follows that of the American Life Panel (ALP). That is, respondents after they insert the amounts, see a summary screen displaying spending by item and the implied total monthly spending. They can then double check and amend the originally provided figures.

experienced the highest number of Covid-19 cases and deaths, and stricter lockdown policies limiting citizens' mobility and engagement in economic activity. In Italy and Spain 36% and 52% of respondents, respectively, express high concerns (7 or above) about the financial consequences of Covid-19. Indeed, these two countries stand out with a significant fraction of households reporting the highest possible level of concern (10). On the other hand, in Germany and the Netherlands the fractions expressing relatively high concerns (above 7) are 25% and 20%, respectively.

It is instructive to explore how financial concern due to Covid-19 varies in our sample. Table 2 reports OLS and ordered probit estimates of the determinants of Covid-19 financial concerns. The explanatory variables include demographic characteristics, occupation dummies, log income, country, and time dummies. Estimated signs line up with our intuition of the potential negative economic consequences of Covid-19. The income coefficient is negative and very precisely estimated, showing that the poor are more concerned than the rich. Liquidity also matters, as having enough resources to make an unexpected payment equal to one month of income reduces the concern about the financial impact of Covid-19 by 1.13 (i.e., 19% of the sample mean).[2]

The age dummies indicate that people in the age group 36-59 are most concerned about the financial consequences of Covid-19, while the young (the reference group), and the oldest age group (60+) are the least concerned. This is quite intuitive, as the latter group mainly consists of retired who are more likely to be insulated from income shocks arising from the crisis. Men are less concerned than women, while the occupation dummies indicate that employed full-time, part-time, and in particular the unemployed are considerably more concerned than those not in the labor force (the reference group).

The country dummies confirm the pattern visible in Figure 1. Namely, respondents in Italy and Spain are more concerned about the financial impact of Covid-19 than those in Germany (the omitted country dummy), while the Dutch are the least concerned. The coefficients of time dummies are all negative, showing that concerns linked to Covid-19 fall in May (relative to the peak of the pandemic in April), and more so in June, July and October.

---

[2] The liquidity dummy is based on the following question: "*Please think about your available financial resources, including access to credit, savings, loans from relatives or friends, etc. Suppose that you had to make an unexpected payment equal to one month of your household income. Would you have sufficient financial resources to pay for the entire amount*?"

The survey includes also a separate question on the health consequences of Covid-19 for the respondent and his or her household.[3] Table A1 in the Appendix relates concern for health to the same set of variables as in Table 2, and results are rather different. Higher education is negatively associated with health-related concern due to Covid-19. On the other hand, the age dummies show that the older (60+) and the middle aged (36-59) are considerably more concerned about the health consequences of Covid-19 compared to the young. Households in Germany (the omitted country) are, once more, less concerned than those in Spain, and the Dutch are concerned the least. Time indicators suggest again that the pandemic-induced concern about health declined from April to July and (to a lesser degree) in October.

Nevertheless, the two Covid-19 variables capturing financial and health-specific concerns are positively correlated (a correlation coefficient of 0.51) and therefore in the econometric analysis we will check if results are robust to controlling in addition for health related Covid-19 concerns.

One would expect that concern about the financial consequences of Covid-19 is negatively associated with consumption for several reasons. First, financial concern depends on current income, liquidity and accumulated wealth, because wealthy households are better equipped to buffer the adverse consequences of the Covid-19 outbreak. Second, financial concerns could be associated with lower income expectations, (e.g. due to the lockdown measures) and depending on the occupation and sector of activity and remote working capability of respondents. Third, financial concerns could reflect an increase in uncertainty about the future, because some households fear a higher probability of becoming unemployed, or because there is uncertainty about the duration of the crisis and the economic consequences of further Covid-19 waves. Financial concerns could also reflect other household idiosyncrasies ranging from, e.g. household composition to concerns about future increases in the tax burden.

In Figure 2 we plot the (log of) monthly non-durable consumption against Covid-19 financial concerns. Comparing those who are least concerned about Covid-19 (values of 2 and below) to those that are very concerned (9 or 10) implies a reduction in consumption by about 25%. Of course, this relation does not consider other variables that

[3] The question is the following: “How concerned are you about the impact of the coronavirus (COVID-19) on your own health or the health of the members of your household?” (coded from 0, not concerned, to 10, extremely concerned).

affect consumption. For this purpose, we will turn to regression analysis in Section 5, exploiting also the panel dimension of the CES.

4.2. Income shock scenarios

A second contribution of our analysis is to explore the potential impact of income shocks that might occur in the future, arising from a second or third Covid-19 wave or associated with government interventions to limit the consequences of the pandemic. Given the different lockdown measures taken in the various countries, and to obtain responses that are broadly comparable across countries, we mimic the effect of a negative income shock using a survey question that refers to an extra tax of 3,000 euro. The second type of income shock is supposed to mimic an income transfer from the government. Although European governments have legislated different income support measures, ranging from unemployment insurance to wage subsidies and once-off Covid-related payments, we rely on a scenario that refers to a generic government bonus. As we shall see, the format of these questions allows us also to compare our results with previous literature.

In particular, the question on the negative income shock refers to a one-time unexpected tax of €3,000, and is asked in a topical module fielded in May:

Imagine you unexpectedly have to make an extra one-time tax payment of €3,000 to the government. In the next 12 months, how would you react to this unexpected reduction in net income? Please allocate the €3,000 over the following four categories:

- *Reduce spending on goods and services that don't last for a long time (e.g. food, clothes, cosmetics, travel, holidays, entertainment, etc.), euro […]*
- *Reduce spending or postpone buying long-lasting goods or services (e.g. a car, home improvement, furniture, electronics, etc.), euro […]*
- *Reduce saving, euro […]*
- *Borrow money or repay less debt, euro […]*
- *Total: should sum to €3,000*

The question on the positive income shock refers to an unexpected bonus of €3,000, and is asked in May and repeated in June to the same households:

Imagine you unexpectedly receive a one-time net payment of €3,000 from the government today. How would you use this unexpected extra income transfer over the next 12 months? Please allocate the €3,000 over the following four categories:

- *Buy goods and services that don't last for a long time (e.g. food, clothes, cosmetics, travel, holidays, entertainment, etc.), euro […]*
- *Buy long-lasting goods and services (e.g. a car, home improvement, furniture, electronics, etc.), euro […]*
- *Save, euro […]*
- *Repay debt, euro […]*
- *Total: should sum to 3,000*

The questions are designed after the exploratory analysis in CJGPV on a sample of Dutch households. They discuss extensively the merits of this format of the questions. First, there is separate information about consumption of non-durables and durables, so one can distinguish between the marginal propensity to consume (MPC) and the marginal propensity to spend (MPS), which includes also durables. Second, there is explicit reference to a time horizon ("in the next 12 months"), hence, one can rule out that differences in the MPC arise from differences in the timing of planned spending. Third, the survey allows characterizing the MPC for positive and negative income shocks (which we denote by MPC+ and MPC-) for the same individual, and therefore to test the hypothesis that the same individual responds more to negative income shocks, as predicted by models with liquidity constraints. Fourth, and similarly to the mostly spend/mostly save questions used by Shapiro and Slemrod (1995), the questions refer to a bonus or to a tax, thus reflecting real life situations. Fifth, the income changes are sizable, as median net household income in the survey, is 2,333 euro per month. Last, to minimize framing we randomly split the sample into two groups and ask the first (second) group the positive (negative) shock question and subsequently the negative (positive) shock question.

The most important difference between the income scenario questions asked in the CES and those used by CGJPR is that in this latter study the questions refer to an amount "equal to one month of income", and respondents are asked to distribute 100 points over the four possible actions. In the CES, instead, the questions refer to a specific amount in euro (3,000), and respondents report how many euro they will allocate to each of the four possible uses. This has two advantages: (i) respondents immediately know the amount of the bonus or the tax, and (ii) it is easier for respondents to allocate in euro the tax or the bonus, rather than to provide a percentage of the tax or bonus among the various uses.

A possible caveat common to all research eliciting subjective behavior in response to various income shock scenarios, is that respondents might in practice display quite different behavior from their reported one (Parker and Souleles, 2019). To gauge the empirical importance of this effect we will therefore compare the analysis of the intention to consume with the analysis of the impact of Covid-19 concerns on realized consumption expenditures.

Figures 3 and 4 show the distributions of MPC+ and MPC- for the six countries of the CES. For MPC- data are available only for May, while data for MPC+ are pooled from the May and June waves. In all six countries the mode of the distribution is zero, and there is clearly some heaping at multiples of 500 in both distributions.

Table 1 reports sample statistics for the CES. In the aggregate, respondents who must pay an unexpected tax of €3,000 would reduce non-durable consumption by €676 (23% of the tax), and durable consumption by €794 (26%). They would also reduce previous wealth by €1,072 (36%) and increase debt by €427 (14%). The impact on consumption and spending out of a positive income shock is lower. In fact, consumers who receive a €3,000 bonus would increase non-durable consumption by €552 (18% of the bonus), and durable consumption by €667 (22%). They would also increase saving by €1,313 (44%) and repay debt by €440 (15%). Overall, there is evidence that the consumption effect of a negative income shock (MPC-) is greater than the effect of positive shock (MPC+). A similar pattern emerges comparing the propensity to spend (MPS->MPS+).

Using only May interviews, one can test formally the hypothesis that MPC-=MPC+. The difference between the two propensities is 3.8 percentage points (8.0 for the marginal propensity to spend), and it is statistically different from zero at the 1% level. At the country level, the test rejects the hypothesis that MPCs from positive and negative shocks are equal at the 1% level in all countries except France. This pattern supports the prediction of models with precautionary saving and liquidity constraints that the average MPC from a negative income shock is higher than that from (an equally sized) positive shock, as found also by CGJPR for the Netherlands.

The only survey that asks similar questions across Euro area countries is the 2017 Household Finance and Consumption Survey (HFCS). In particular, the HFCS asked a single question on a positive income shock (a lottery win equal to one month of income), without distinction between consumption of durables and non-durables, thus eliciting the marginal propensity to spend. Drescher et al. (2020) report the country-level statistics for the 17 countries in the HFCS for which information on MPS+ is available, and estimate the relation between income, wealth and MPS+.

For the countries included in the CES, one can compare the MPS+ with the HFCS (except for Spain where this question was not asked), bearing in mind that the two surveys have been fielded in periods with markedly different economic conditions. The two MPS+ estimates might also differ because the format of the question is not identical (i.e. 3000 euro vs. a shock proportional to income). Nevertheless, the MPS+ are of similar order of magnitude in Germany, France and the Netherlands. Differences could also be attributed to the different context and timing (2017 in the HFCS and the mid of the Covid-19 crisis in the case of the CES). Appendix Table A2 shows that MPS+ in the two surveys are approximately equal in the Netherlands (the country with the least financial concerns due to Covid), while according to the CES results in 2020 it is considerably lower in Italy (the most concerned country together with Spain).

Figure 4provides a graphical analysis of the relation between concerns for the financial impact of the pandemic and the four estimated propensities (MPC+, MPC-, MPS+, MPS-).The upper-left and lower-left graphs indicate that MPC- and MPS- are strongly and negatively related to financial concerns due to Covid-19. Comparing the lowest and highest concerns implies an increase in MPC- by about 10 percentage points. Because we are considering a negative income shock, the positive relations apparent in Figure 5 imply a stronger (more negative) consumption effect of a negative income shock for those who have higher concerns about the household's financial situation due to Covid-19.

In the upper-right and lower-right graphs we plot MPC+ and MPS+ against the financial concern due to Covid-19. In this case, there is no or little association between the reaction to a positive income shock and Covid-19 concerns. As we shall see, the econometric estimates broadly confirm the patterns shown in Figure 5.

5. Econometric estimates

In this Section we present two main sets of results. In Section 5.1 we associate concerns for the financial impact of Covid-19 to the level of consumption, controlling for unobserved heterogeneity. In Section 5.2 we associate the same variable to the MPC and the MPS from positive and negative income shocks.

5.1. Financial concerns due to Covid-19 and consumption

Using panel data from April, July and October , we regress log consumption of non-durables on financial concern due to Covid-19, age, education and employment dummies, gender, family size, household resources (income and access to liquidity), country and time dummies. In the first regression we model unobserved heterogeneity with random effects, and in the second regression we use fixed effects. Of course, in the latter we cannot estimate the effect of variables that don't change between April and October, and in some cases even the variables that change over time have limited variability, resulting in relatively large standard errors.

Our main coefficient of interest is concern about the household's financial situation due to Covid-19, which is negative and statistically different from zero at the 1% level in both the random effects and fixed effects specifications (see Table 3). The negative association between the two variables is also economically significant, that is, raising concern from 0 (the least concerned) to 10 (the most concerned), reduces consumption by 6.9 percent in the regression with random effects, and by 13.7 percent in the regression with fixed effects. As regards other variables, liquidity (the ability to have access to enough liquid resources to make an unexpected payment equal to one month's income), is associated with 10% higher consumption in both specifications.

Interestingly, when examining the concern about one's own health as well as the health of other household members on spending, we find that it has no statistically significant effect in the fixed effects specification. This result is not surprising and suggests that own health concerns have no independent impact on consumption but instead works via the channel associated with financial concerns. This suggests that the precautionary saving motive behind the financial concern is a much stronger independent driver of spending behavior than the health-related concern per se. Indeed, while the precautionary saving motive should necessarily reduce spending, if one is concerned about health one may even increase spending for some items (e.g. by using more frequently private cars or taxis instead of public transportation, or by working more from home and thus spending to make the necessary arrangements).

The fixed effects estimates are clearly preferable to the cross-sectional ones as they eliminate time-invariant unobserved household heterogeneity. However, they could still be biased due to confounding caused by time-varying unobservable factors affecting both Covid-19 financial concerns and consumption. Therefore, one cannot claim causality from the mere negative association between the two variables. We will tackle this important issue in Section 6.

5.2. Financial concerns for Covid-19 and the propensity to consume and spend

In Table 4 we report estimates of the effect of financial concern on the MPC and MPS from positive and negative income shocks. Since the MPC and MPS variables are truncated at zero and one, we report marginal effects obtained from two-limit Tobit estimates. In each regression we control for the Covid-19 variable, for demographic variables and for household resources (income and liquidity). While for MPC- and MPS- we can use only May wave observations, for MPC+ and MPS+ we can perform panel estimation with fixed effects, as the question is repeated also in June. Table 4 focuses on the coefficient of the "Concern for Covid-19", while the full set of estimates is reported in Appendix Tables A3 and A4.

Regressions for MPC- and MPS- show that concern for Covid-19 is positively and significantly associated with the propensity to consume and spend, a result also apparent in Figure 5. The effect is also economically significant: comparing individuals who are least concerned about Covid-19 with those that are extremely concerned is associated with an increase in the MPC- of 5 percentage points (4.1 points for MPS-). Although the question refers to a generic income drop of 3,000 euro, one could interpret it also as a possible consumption effect during a lockdown and associated income drop during a second or third wave of the pandemic. The important implication of these findings is that concern for Covid, as it is associated with a rise in both the MPC- and the MPS-, will tend to amplify the negative consumption impact of any reduction in income.

The coefficient of concern for Covid-19 in the regressions for MPC+ is small and not statistically different from zero in both Tobit and fixed effects estimates. However, in the regressions for MPS+ the coefficient is negative and statistically different from zero. It is relatively small in the Tobit estimates (which do not account for time invariant unobserved heterogeneity) and larger in absolute value in the fixed effects estimates (-

0.0042). The latter suggests that the total spending response to positive income shocks is dampened by Covid-19 concerns, another indication of a precautionary saving effect.

This finding has implications for the effectiveness of positive income transfers aimed at stabilizing consumption during the pandemic. For example, households with relatively high Covid-19 concerns would require a proportionately larger income transfer to achieve a given consumption response. Recalling the previous evidence on the cross-country and cross-sectional heterogeneity in Covid-19 financial concerns, this would point toward the need for larger fiscal support measures in Italy and Spain and potentially more targeted measures aimed at households in the 36-59 age group, unemployed households or households who are liquidity constrained. The finding that financial concerns due to Covid-19 are associated only with MPS+ and not with MPC+ suggests that such targeted measures would mainly derive from their impact on durable consumption rather than via the effect on non-durables.

Results also suggest an important role for liquidity. In particular, having liquid assets reduces MPC- and MPS- (i.e., it moderates the drop in consumption due to the negative shock), while it increases MPC+ and MPS+.

Overall, the regressions for MPC and MPS show that financial concerns due to Covid-19 amplify the negative consumption response to income drops and attenuate the positive consumption response to income gains. Both effects are broadly consistent with models in which precautionary saving matters for consumption decisions.

6. Partial identification

The estimates of the effect of the financial concern due to Covid-19 on spending that we have obtained up to now, while economically plausible, could still suffer from endogeneity and/or spurious correlation problems due to time-varying unobserved factors that may influence both the pandemic-induced financial concern and spending decisions. Such factors could include changing working arrangements or interactions with one’s social network, and both have indeed changed during the pandemic. In principle, one could counter this endogeneity problem by using an exogenous instrumental variable (XIV), but it is hard to think of a plausible XIV in our context. Moreover, when treatment effects are heterogeneous, an XIV will identify the effect of interest only for compliers, that is, for respondents who change their pandemic-induced financial concern due to a change in the XIV. This subsample of respondents could well be a specific one, while we are interested in drawing inferences for the entire population.

6.1 Methodology[4]

To deal with the potential endogeneity problems we use the PI methods introduced by Manski (1989, 1990, 1994). PI methods are nonparametric and produce bounds on the average treatment effect (henceforth ATE). That is, they locate the ATE in an identification region instead of producing a point estimate. Furthermore, PI has various important advantages over OLS and IV methods, as discussed below. In what follows, we give a brief overview on how we implement PI methods in our context and provide additional details in Appendix A.1.

PI methods apply bounds to the counterfactual, and thus unobservable, average potential outcomes across sample units. An example of such a counterfactual outcome would be, for those who report that they are not concerned, the average spending of their household had they been very concerned. To estimate the average spending when all individuals in the sample are very concerned, we need to calculate this counterfactual outcome and compare it with the corresponding average spending when nobody is concerned. This comparison will allow us to calculate the ATE of a change from not being concerned to being very concerned. If one does not use any assumptions, then one can credibly use as a lower (upper) bound of the counterfactual only the minimum (maximum) feasible values of the outcome. Clearly, these extreme values result in very wide and thus uninformative identification regions (we provide additional details on bounds using no assumptions in Appendix A.2). Hence, to informatively bound unobserved counterfactual outcomes, PI uses assumptions that are, as we will see, much milder than those used in OLS- and XIV-based methods.

The first assumption is that of monotone treatment response (MTR henceforth; see Manski, 1997), which in our context states that spending is, on average, weakly decreasing in the pandemic-induced concern about one's financial situation. This average weakly monotonic relationship holds for potential outcomes, and thus is unverifiable. MTR is, however, a reasonable assumption in our context because greater financial

[4] The description in this section is based on Christelis et al. (2020) who employ PI to estimate bounds on the coefficient of relative prudence.

concern is, on average, likely to lead (some households) to more precautionary saving, and thus to lower spending. We emphasize here that the MTR assumption posits that the weakly negative relationship between financial concern and spending holds *on average*. In other words, while there could well be households who for idiosyncratic reasons might increase their spending when they are more concerned about their financial situation, the assumption postulates that such households are a minority in the population.

Importantly, MTR posits a weakly negative association, and thus it fully allows the pandemic-induced financial concern to have, on average, no effect on spending whatsoever. Hence, the MTR assumption is not sufficient for estimating a negative effect on spending, as will be shown in Table 5 below. As an example of the operation of the MTR assumption, suppose one would like to bound the counterfactual mean spending of those who are not concerned about Covid-19, had they been very concerned. Under MTR, an upper bound for this counterfactual outcome is the actual mean spending of those who are not concerned. This upper bound is obviously much smaller than the maximum feasible value of spending, and thus leads to narrower identification regions. We further discuss the MTR assumption in Appendix A.3.

The second identification assumption is that of Bounded Variation (BV henceforth), introduced by Manski and Pepper (2018). We use BV to bound counterfactual outcomes that cannot otherwise be bounded using MTR. BV posits that the counterfactual outcome can differ by an observed outcome by up to a specified amount. For example, the unobserved counterfactual mean spending of those who are actually not concerned by Covid-19 had they been very concerned can be bounded from below by something more informative than the minimum feasible value. We thus posit that it can be bounded from below by a multiple of the standard deviation of spending. As there is no clear guidance on how large this multiple can be, we present results for various values of this multiple, and let readers choose which values lead to more credible identification regions. Importantly, the BV assumption does not affect the estimate of the minimum (in absolute value) influence of the treatment (i.e., by at least how much the pandemic-induced concern reduces spending) but only the maximum influence (i.e., by at most how much the concern affects spending). We further discuss the BV assumption in Appendix A.4

The third assumption we use is the monotone instrumental variable (MIV henceforth) one, which was introduced by Manski and Pepper (2000) and serves to further narrow ATE identification regions (we discuss the MIV assumption further in Appendix A.5). The assumption posits that the instruments are weakly monotonically associated with the outcome, namely spending. Specifically, it posits that the average potential outcomes are weakly increasing for those with observed higher MIV values. This is a much milder assumption than that of exogeneity in a standard XIV setup, and it is made even milder by the allowed possibility (under weak monotonicity) that the MIV has no association, on average, with the outcome. Crucially, the MIV assumption identifies the ATE and not the local average treatment effect (LATE, i.e., the effect for those whose financial concern changes due to a change in the XIV). One can thus interpret PI results as applying to the whole population.

We use age as an MIV for spending, conditional on income. In other words, we posit that, controlling for income, older households, on average, spend at least as much (and thus save less) as their younger counterparts. This can be justified on standard life-cycle theory grounds, that is, due to the income drop the elderly dissave or save less to smooth consumption over time. Importantly, as is also the case with MTR, the MIV assumption needs to hold on average, that is, it allows for the possibility that a minority of households increase their saving as they age, controlling for income.

The MIV assumption (like the MTR) refers to potential outcomes, and thus is unverifiable (as is the case with standard XIVs). In the CES, as evidenced by the results for spending shown in Table 3, there is a strong positive association between spending and age. This is not a proof that the MIV assumption holds, as these estimated associations refer to observed data and not to potential outcomes. However, this observed association points clearly to the same direction as the MIV assumption.

We use age as an MIV also for the MPCs (conditional on income and country), using the results in CGJPR. Specifically, in intertemporal models with finite horizons and liquidity constraints, the authors show that the MPCs out of both positive and negative income shocks are increasing in age. The reason is that older households have less time to smooth their consumption in response to an income shock. In our data, as reported in Appendix Table A3, we observe no significant association of age with MPC-. This is fully allowed by the MIV assumption, which posits a weakly monotonic positive association between age the MPCs. As for the MPC+ and MPS+, we observe in Appendix Table A4 a negative association between the MPC+ and age, and a positive one between MPS+ and age. The former result, while not disproving the MIV assumption as it refers to observed data, is not congruent with it. Hence, we need to interpret the results on this MPC with caution. On the other hand, the observed positive association between age and MPS+ is quite congruent with the MIV assumption.

In all specifications we contrast the PI estimates with those obtained under exogenous treatment selection (ETS henceforth), which posits that respondents receiving different treatments are not systematically different from one another. In other words, ETS implies that concern for Covid-19 is as good as randomly assigned across households. Hence, the ATE under ETS is equal to the difference in observed mean outcomes, conditional on different values of the financial concern.

To implement PI, we need to discretize the treatment variable. We thus create a binary variable denoting the concern for Covid-19 "equal or below" and "above" the median. We then evaluate the bounds of the average potential outcomes at each of the two levels. To conduct inference on the ATE bounds we compute 95% bias-corrected bootstrap percentile confidence intervals, (CIs henceforth; see Efron, 1982), using 10,000 bootstrap replications.

The advantages of PI are considerable, and we discuss them in further detail in Appendix A.6. First, it uses mild assumptions (MTR, MIV and BV in our case), especially compared to the exogeneity ones required in OLS and XIV estimation. Second, it is nonparametric. Third, PI allows unlimited heterogeneity in any variable, observable or not, affecting the outcome (e.g., in our context, preferences, expectations, and health, workplace, or family problems). Fourth, PI provides estimates of the ATE (and not the LATE) and allows for full heterogeneity across sample units. Fifth, as we shall see, PI is completely transparent about how each assumption affects estimates.

On the other hand, PI can sometimes lead to identification regions that are wide. As Manski (1994) notes, however, the point identification obtained using the assumptions of OLS and XIV may give false confidence about empirical results, as the reduction in uncertainty is obtained through strong and untestable assumptions that might not hold in the real world.

6.2. PI results

6.2.1 PI results for realized consumption

Table 5 reports the PI regions of the ATEs of the pandemic-induced financial concern on the logarithm of spending (thus, ATEs denote semi-elasticities) in three different panels that capture a change in financial concern for Covid-19 from the median and below to above the median. For every estimation method, we report the lower and upper bounds of the ATE (or, in the case of ETS, the point estimate), as well as the 95% CIs for the lower and upper ATE bounds.

We first examine the ETS estimates, which in practice can be obtained by running a weighted OLS regression on a constant and a dummy variable denoting concern for Covid-19 above the median. The ETS results imply that financial concern has a strong negative effect on spending, with an estimated semi-elasticity that is equal to -0.12. We also note that the CIs around the ETS estimates are relatively narrow.

PI relaxes the assumption of exogeneity of concern for Covid-19 that underlies the ETS estimates. When using no assumptions whatsoever, and thus bounding counterfactual outcomes with the minimum and maximum feasible outcome values, we predictably obtain very wide and uninformative ATE identification regions. We report this result only to illustrate the point that one cannot draw any useful conclusions about causal effects with data on their own and without any further identification assumption

When introducing the MTR assumption, the upper ATE bound becomes zero, while the lower ATE bound remains uninformative. Hence, MTR on its own does allow one to reject the null hypothesis that concern for Covid-19 has no effect on spending. We also note that the ATE lower bound CI has both its upper and lower bound equal to zero, which implies that the constraint that the ATE is non-positive imposed by the MTR assumption is binding in at least 95% of the bootstrap runs.

When using the MIV together with the MTR assumption the ATE upper bound is now below 0, and equal to -.0277 (95% CI: -0.046, -0.026). In other words, when concern changes from the median level or below to above the median, consumption drops by at least 2.77%. This semi-elasticity is equal to about 0.04 standard deviations of log spending, and is economically important when one considers that aggregate data suggest that household spending dropped by about 10% on average in the second quarter of 2020 compared to the second quarter in 2019 for the countries in our sample. On the other hand, the ATE lower bounds are uninformative in all cases. In the absence of an informative lower bound one could potentially use the ETS semi-elasticity estimate of -0.12 as a substitute, if one assumes that the ETS results overstate the ATE.

To gauge how a lower ATE bound of 0.0277 compares with the fixed effects results shown in Table 3, we first note that the fixed effects point estimate is equal to -0.0137. Given that the median difference in the financial concern between sample units in the two levels of the binary concern variable is equal to 3, when we multiply 0.0137 by 3 we obtain -0.041, and thus the discrete analog of the fixed effects estimate is contained in the MTR+MIV identification region. Importantly, however, this ATE identification region is robust also to unobservable time-varying factors leading to treatment selection, whereas the fixed effects estimate is not.

Finally, we introduce BV assumptions using as multiples 20%, 25% and 30% of the standard deviations of mean spending. These multiples seem reasonable given that the ATE upper bound is 0.04 standard deviations as already discussed, and we let readers decide which multiples they find most credible. We note that the BV assumption has no effect on the ATE upper bounds but makes the ATE lower bounds much more informative, ranging from -0.10 to -0.17 for the change from in the concern for Covid-19 variable from the median or below to above the median.

6.2.2 PI results for the propensity to consume and spend

We turn now to the PI results for MPC- and MPS-, which are shown in Panels A and B of Table 6. The pattern of MPC- results is similar to that for actual log consumption: ETS estimates are strongly positive in the case of MPC-, that is, they make the drop in consumption due to a negative income shock larger. Bounds derived using no assumptions remain uninformative.

Introducing MTR makes the ATE lower bounds equal to 0, while upper bounds remain uninformative. Combining MTR with MIV, however, produces informative lower bounds equal to about 1.9 percentage points (95% CI: 1.7, 3.3) for the MPC- and about 3.1 percentage points (95% CI: 2.7, 5.3) for the MPS-. These magnitudes denote that spending will be reduced by at least this much due to a negative shock, and they are economically important, as they represent about 0.074 and 0.085 standard deviations of the respective outcomes.

Finally, when adding the BV assumption, ATE upper bounds become much more informative again, while ATE lower bounds remain unaffected. For a treatment change from the median or below to above the median the ATE upper bounds range from about 7.4 to about 10.1 percentage points in the case of the MPC-, and from 12.2 to about 16 percentage points for MPS-.

We show results for MPC+ and MPS+ in Panels D and C of Table 6. ETS estimates are not statistically significant for the case of the MPC+, a result which is congruent with the lack of a positive association between the outcome and the treatment shown in Figure 5. On the other hand, ETS estimates for the MPS+ are negative (equal to -2.77 percentage points) and statistically significant. They imply that concern for Covid-19 reduces the increase in spending due to a positive income shock, which is what one would expect if financial concern induces precautionary saving.

As expected, identification regions derived using no assumptions remain uninformative. Adding MTR makes the ATE upper bounds equal to 0, while lower bounds remain uninformative. Combining MTR with MIV, leads to an informative ATE upper bound equal to about -1.27 percentage points (95% CI: -2.17, -1.02) in the case of the MPC+. As discussed in Section 6.1, however, we need to interpret this result with caution, given that the MIV assumption might not be consistent with the patterns in the data. If one does not find the MIV assumption credible, then one must stop at the MTR results, which imply that one cannot reject the null that the concern for Covid-19 has no effect on the MPC. Readers can readily make such a choice because PI methods very transparently show how each assumption affects results.

As regards the MPS+, the MTR+MIV upper bound is equal to -1.04 percentage points (95% CI: -2.19, -1.02). The magnitude of this upper bound corresponds to about 0.038 standard deviations, while that of the corresponding upper bound on the MPC+ is 0.05 deviations. Hence, while both magnitudes are economically relevant, they are smaller than in the case of propensities to consume or spend out of negative income shocks.

Finally, adding the BV assumption leads once again to much more informative ATE lower bounds, while ATE upper bounds remain unaffected. In particular, the ATE lower bounds on the MPC on nondurables range from -5.7 to -8 percentage points, while for the MPC on the sum of non-durables and durables they range from -6.1 to -9.7 percentage points.

All in all, the PI results are aligned with the results presented in Section 5, although they involve increased identification uncertainty due to the milder assumptions used to generate them. They confirm that a larger concern about the household's financial situation manifests itself in reduced actual spending in line with increased precautionary behavior, larger spending drops in the case of a negative income shock and smaller spending increases in the case of a positive shock.

7. Summary

The paper uses novel panel data from the Consumer Expectations Survey (CES) to examine whether the concern about the household's financial situation due to Covid-19 affects spending. The panel spans, with monthly observations on about 10,000 households from six Eurozone countries, the pandemic crisis from April to October 2020. The paper makes several contributions to the literature. First, it offers new evidence on the consumption response to the Covid-19 outbreak in six eurozone countries. To that effect, the paper uses a household-specific measure of financial concerns due to Covid-19 and employs different estimation techniques (panel fixed effects and partial identification methods) that provide results that are robust to time-invariant and time-varying unobserved factors that can lead to treatment selection. Second, it explores the implications of pandemic-induced financial concerns for the consumption responses to positive and negative income shock scenarios.

The paper offers several important insights about the economic effect of the Covid-19 outbreak. It finds a negative and statistically significant effect of financial concern due to Covid-19 on non-durable consumption. The negative association between the two variables is also economically significant, that is, raising concern from 0 (the least concerned) to 6 (the median concern), reduces consumption by 8.2 percent in regressions with fixed effects. These results are corroborated using partial identification methods that generate informative identification regions under weak assumptions. As estimation controls for current income, socio-economic variables, household unobserved heterogeneity and aggregate effects, precautionary saving is a natural explanation for the negative association between concerns for the financial consequences of Covid-19 and consumption.

The paper also explores the potential impact of income shocks that might occur in the future, arising from a second Covid-19 wave or associated with government interventions to limit the consequences of the pandemic. Overall, concern for Covid-19 amplifies the negative consumption response to income reductions and attenuates the positive consumption response to income increases. Both effects are broadly consistent with models in which precautionary saving matters for consumption decisions.

The finding that financial concerns due to Covid-19 are not uniformly distributed in the population but affect more the behavior of certain population subgroups suggests that there is scope for targeted government support measures. Easing pandemic-related financial concerns can counter the observed drop in spending and reduce the consumption adjustment in response to any new negative income shock. The results imply also that fiscal measures will tend to be more effective if they are targeted at relatively younger, liquidity constrained households and households with less stable employment conditions who exhibit the highest Covid-19 related financial concerns and the highest marginal propensities to consume out of possible fiscal transfers. In addition, such concerns tend to reduce consumption by more when income shocks are negative than it increases it when shocks are positive implies that to fully counter-balance the effects on spending, governments need to support the income of households who have experienced negative income shocks by an amount that is *larger* than the shock itself. If current strains on government budgets make large transfers unlikely, the observed drop in spending during the pandemic is likely to persist for as long as households are concerned about their finances.

References

Andersen, Asger, Emil Toft Hansen, Niels Johannesen and Adam Sheridan (2020), "Consumer Responses to the COVID-19 Crisis: Evidence from Bank Account Transaction Data," Covid Economics 7, 88-114.

Armantier, Olivier, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar (2016), "An Overview of the Survey of Consumer Expectations," Federal Reserve Bank of New York Staff Reports No. 800.

Baker, Scott R., R.A. Farrokhnia, Steffen Meyer, Michaela Pagel and Constantine Yannelis, (2020), "How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic," Covid Economics 18, 73-108.

Bounie, David, Youssouf Camara and John W. Galbraith (2020), "Consumers' Mobility, Expenditure and Online-Offline Substitution Response to COVID-19: Evidence from French Transaction Data," CIRANO Working Papers 2020-28

Bunn, Philip, Jeanne Le Roux, Kate Reinold, Paolo Surico (2018), "The Consumption Response to Positive and Negative Income Shocks," *Journal of Monetary Economics* 96, 1-15.

Carroll, Christopher D. (1996), "A Theory of the Consumption Function, With and Without Liquidity Constraints," J*ournal of Economic Perspectives* 15, 23-46.

Carvalho, Bruno P., Susana Peralta and Joao Pereira (2020°), "What and How did People Buy during the Great Lockdown? Evidence from Electronic Payments," Covid Economics 28, 119-158.

Carvalho, Vasco, M., Stephen Hansen, Álvaro Ortiz, Juan Ramón García, Tomasa Rodrigo, Sevi Rodríguez Mora, and José Ruiz (2020b), "Tracking the COVID-19 Crisis with High Resolution Transaction Data," CEPR Discussion Paper 14642.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team (2020), "How did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-time Economic Tracker Based on Private Sector Data," https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf

Christelis, Dimitris, Dimitris Georgarakos, Tullio Jappelli, Luigi Pistaferri, Maarten van Rooij (2019), “Asymmetric Consumption Effects of Transitory Income Shocks,” *The Economic Journal* 129, 2322–2341.

Christelis, Dimitris, Dimitris Georgarakos, Tullio Jappelli, Maarten van Rooij (2020), “Consumption Uncertainty and Precautionary Saving,” *Review of Economics and Statistics* 102, 148-161.

Chronopoulos, Dimitris K., Marcel Lukas and John O.S. Wilson (2020), “Consumer spending responses to the Covid-19 pandemic: An assessment of Great Britain,” *Covid Economics* 34, 145-186.

Cox, Natalie, Peter Ganong, Pascal Noel, Joseph Vavra, Arlene Wong, Diana Farrell, and Fiona Greig (2020), “Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data,” *Brookings Papers on Economic Activity*, forthcoming.

Drescher, Katharina, Pirmin Fessler, Peter Lindner (2020), “Helicopter Money in Europe: New Evidence on the Marginal Propensity to Consume across European Households,” *Economic Letters* 1195, https://doi.org/10.1016/j.econlet.2020.109416

Deaton, Angus, (1991), “Saving and Liquidity Constraints,” *Econometrica* 59, 1221-48.

Dunn, Abe, Kyle Hood, and Alexander Driessen (2020), “Measuring the Effects of the COVID-19 Pandemic on Consumer Spending using Card Transaction Data,” BEA Working Paper 2020-5, Bureau of Economic Analysis.

ECB (2020), The ECB’s Consumer Expectations Survey: A First Evaluation, forthcoming, ECB Occasional Paper Series.

Efron, Bradley (1982), *The Jackknife, the Bootstrap, and Other Resampling Plans,* Philadelphia: Society for Industrial and Applied Mathematics.

Fuster, Andreas, Greg Kaplan, Basit Zafar (2018), “What Would You Do With $500? Spending Responses to Gains, Losses, News and Loans,” NBER Working Paper No. 24386.

Georgarakos, Dimitris and Geoff Kenny (2020), “Euro Area Household Sector Adjustment during the Global Pandemic: Insights from a New Consumer Survey, *mimeo*, European Central Bank.

Granja, Joao, Christos Makridis, Constantine Yannelis, and Eric Zwick (2020), "Did the Paycheck Protection Program hit the Target?" NBER Working Paper No. 27095.

Guiso, Luigi, Tullio Jappelli, and Luigi Pistaferri (2002), "An Empirical Analysis of Earnings and Employment Risk, *Journal of Business and Economic Statistics* 20, 241-253.

Hacioglu, Sinem, Diego Känzig and Paolo Surico (2020), "Consumption in the Time of Covid-19: Evidence from UK Transaction Data," CEPR Discussion Paper 14733.

Jappelli, Tullio, Luigi Pistaferri (2014), "Fiscal Policy and MPC Heterogeneity," *American Economic Journal: Macroeconomics* 6, 107-36.

Jappelli, Tullio, Luigi Pistaferri (2020), "Reported MPC and Unobserved Heterogeneity," *American Economic Journal: Economic Policy,*

Kaplan Greg, Giovanni L. Violante (2014), "A Model of the Consumption Response to Fiscal Stimulus Payments," *Econometrica* 82, 1199–1239.

Manski, Charles F. (1990), "Nonparametric Bounds on Treatment Effects," *American Economic Review Papers and Proceedings* 80, 319-323.

Manski, Charles F. (1994), "The Selection Problem," in Advances in Econometrics: Sixth World Congress, C. Sims ed. Cambridge, UK: Cambridge University Press.

Manski, Charles F. (1997), "Monotone Treatment Response," *Econometrica* 65, 1311-1334.

Manski, Charles F., and John V. Pepper (2000), "Monotone Instrumental Variables, with an Application to the Returns to Schooling," *Econometrica* 68, 997-1012.

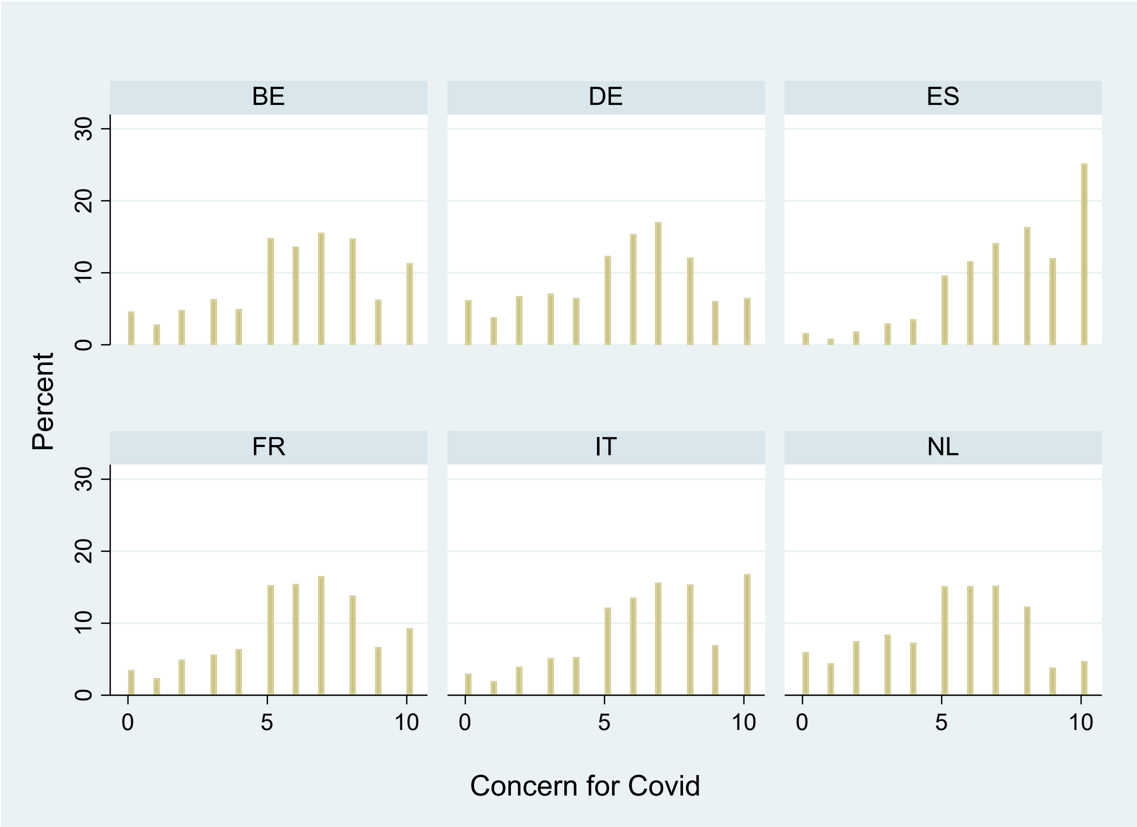
Manski, Charles F., and John V. Pepper (2018), "How Do Right-to-Carry Laws Affect Crime Rates? Coping with Ambiguity Using Bounded Variation Assumptions," *Review of Economics and Statistics* 100, 232–244.

Parker, Jonathan A., and Nicholas S. Souleles (2019), "Reported Effects versus Revealed-Preference Estimates: Evidence from the Propensity to Spend Tax Rebates," *American Economic Review: Insights* 1, 273-90.

Shapiro, Matthew D., Joel Slemrod (1995), "Consumer Response to the Timing of Income: Evidence from a Change in Tax Withholding," *The American Economic Review* 85, 274-283.

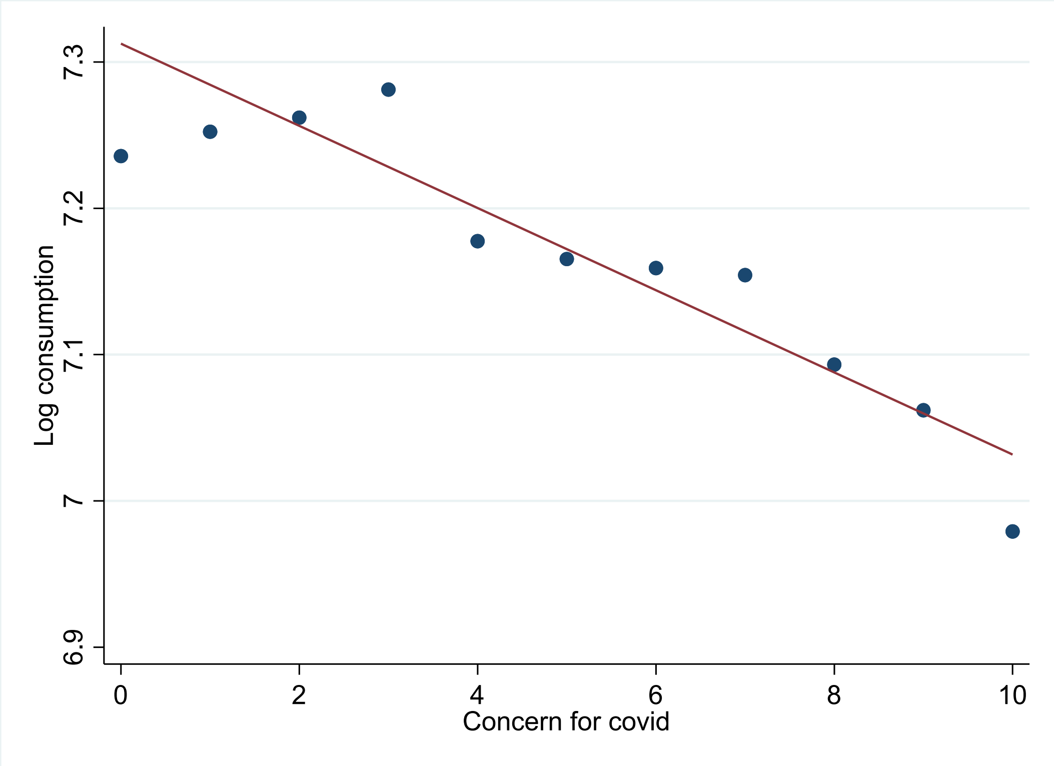
Shapiro, Matthew D., Joel Slemrod (2009), "Did the 2008 Tax Rebates Stimulate Spending?" *American Economic Review Papers and Proceedings* 99, 374-379.

Figure 1. The distribution of the concern about the household's financial situation due to Covid-19



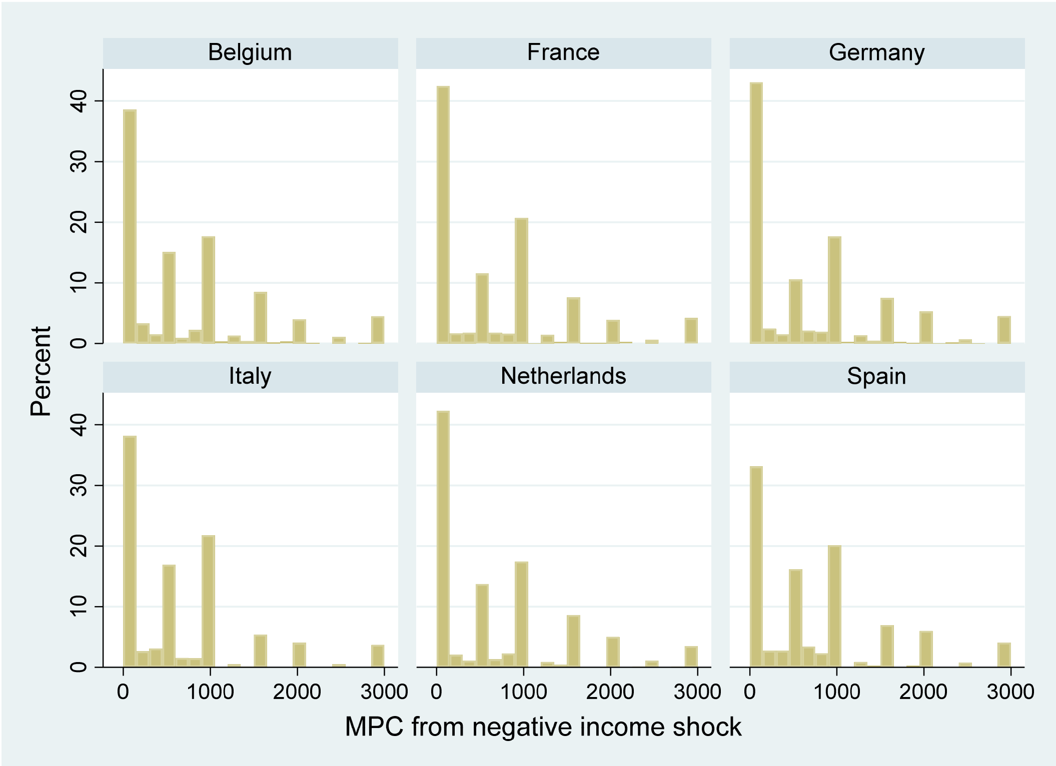
Note. Data are drawn from the April, July, and October waves of the CES.

Figure 2. Concern about the household's financial situation due to Covid-19 and consumption



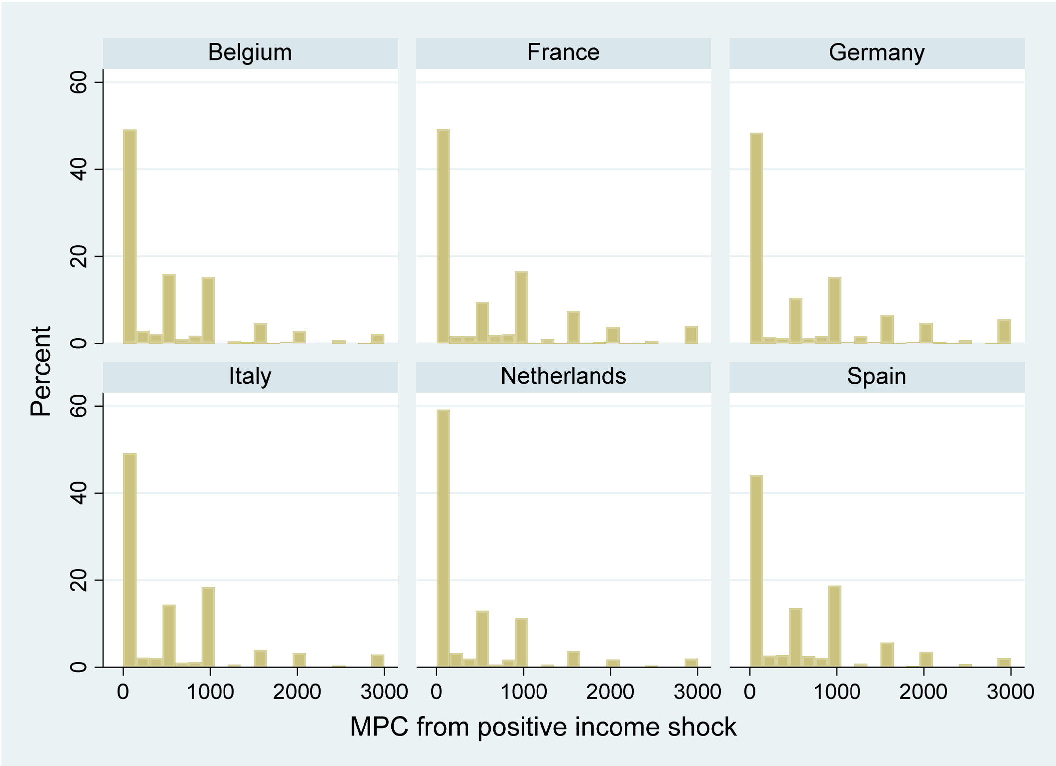
Note. The figure plots the concern about the household's financial situation due Covid-19 against the natural logarithm of monthly non-durable consumption. Data are binned. Data are drawn from the April, July, and October waves of the CES.

Figure 3. Consumption response to a negative income shock, non-durables



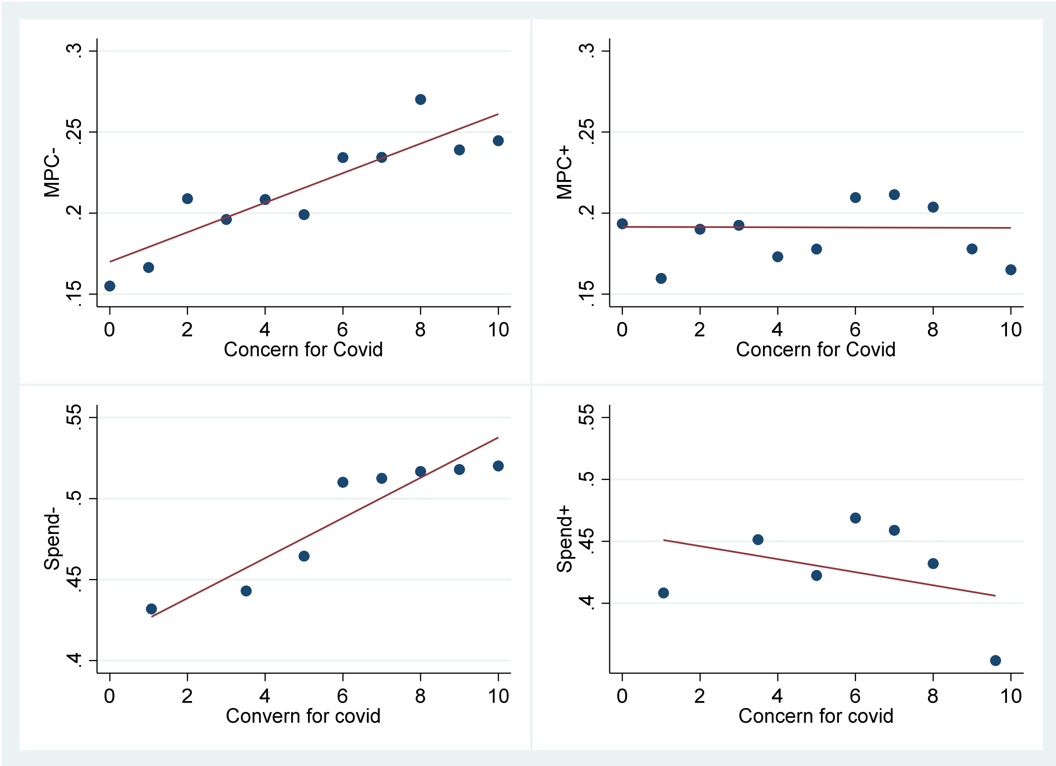
Note. Data are drawn from the May wave of the CES.

Figure 4. Consumption response to a positive income shock, non-durables



Note. Data are drawn from the May and June waves of the CES.

Figure 5. Concern about the household's financial situation due to Covid-19 and the marginal propensity to consume



Note. The figure plots the MPCs for non-durables (denoted by MPC) and the sum of durables and non-durables (denoted by Spend) due to negative and positive income shocks against the concern about the households' financial situation due Covid-19. Data are binned. Data are drawn from the May and June waves of the CES.

Table 1. Descriptive statistics

Variable	Statistic
Monthly consumption of non-durables (PPP-adjusted)	1,301.7
Negative income shock	
Reduction of spending on non-durables	0.227
Reduction of spending on durables	0.264
Total reduction of spending	0.491
Reduction of saving	0.356
Increase in debt	0.144
Positive income shock	
Increase in spending on non-durables	0.191
Increase in spending on durables	0.233
Increase in total spending	0.424
Increase in saving	0.424
Reduction of debt	0.142
Concern due to Covid-19 about financial situation	6.08
Concern due to Covid-19 about health	6.54
Age	50.0
Male respondent	0.48
Household Size	2.56
Secondary education	0.32
Tertiary education	0.53
Annual household income (PPP-adjusted)	30,000.0
Belgium	0.04
Germany	0.30
Spain	0.17
France	0.22
Italy	0.22
Netherlands	0.06
April wave	0.20
May wave	0.20
June wave	0.20
July wave	0.20
October wave	0.20

Notes. The table reports medians for consumption and income, means for all other variables. Data are drawn from the April, July, and October waves of the CES.

Table 2. Determinants of the concern about the household's financial situation due to Covid-19

Variable	OLS			Ordered probit		
	Coeff.	Std. Error	p-value	Coeff.	Std. Error	p-value
Age 36-59	0.171	0.048	0.000	0.083	0.020	0.000
Age 60+	-0.102	0.067	0.127	-0.026	0.027	0.339
Household size	0.104	0.017	0.000	0.042	0.007	0.000
Male financial respondent	-0.203	0.041	0.000	-0.086	0.017	0.000
Secondary education	-0.070	0.064	0.273	-0.030	0.027	0.268
Tertiary education	-0.087	0.059	0.142	-0.041	0.026	0.112
Employed full-time	0.242	0.064	0.000	0.108	0.026	0.000
Employed part-time or on extended leave	0.219	0.067	0.001	0.105	0.027	0.000
Unemployed	0.579	0.072	0.000	0.270	0.031	0.000
Log of household income	-0.397	0.031	0.000	-0.171	0.013	0.000
Has liquidity	-1.132	0.041	0.000	-0.507	0.018	0.000
Belgium	0.371	0.083	0.000	0.142	0.033	0.000
Spain	1.602	0.067	0.000	0.687	0.028	0.000
France	0.408	0.065	0.000	0.146	0.025	0.000
Italy	0.680	0.069	0.000	0.273	0.027	0.000
Netherlands	-0.316	0.085	0.000	-0.139	0.032	0.000
May wave	-0.226	0.029	0.000	-0.099	0.012	0.000
June wave	-0.522	0.032	0.000	-0.220	0.014	0.000
July wave	-0.552	0.032	0.000	-0.232	0.014	0.000
October wave	-0.458	0.033	0.000	-0.192	0.014	0.000
Constant	10.419	0.314	0.000	-..-	-..-	-..-
Number of observations			39,805			

Notes. OLS and ordered probit coefficients shown. Data are drawn from the April, July, and October waves of the CES.

Table 3. Concern about the household's financial situation due to Covid-19 and consumption: results from panel data OLS models

Variable	Random effects OLS			Fixed effects OLS		
	Coeff.	Std. Error	p-value	Coeff.	Std. Error	p-value
Concern about the household's financial situation due to Covid-19	-0.0069	0.002	0.000	-0.0137	0.003	0.000
Concern about own and household member's health due to Covid-19	0.0042	0.002	0.041	0.0006	0.003	0.826
Age 36-59	0.1507	0.014	0.000	-..-	-..-	-..-
Age 60+	0.2205	0.018	0.000	-..-	-..-	-..-
Household size	0.0963	0.005	0.000	-..-	-..-	-..-
Male financial respondent	0.0078	0.011	0.478	-..-	-..-	-..-
Secondary education	-0.0010	0.017	0.951	-..-	-..-	-..-
Tertiary education	0.0583	0.016	0.000	-..-	-..-	-..-
Employed full-time	0.0465	0.017	0.006	0.0200	0.038	0.597
Employed part-time or on extended leave	0.0406	0.017	0.015	-0.0194	0.029	0.505
Unemployed	-0.0154	0.020	0.432	-0.0262	0.035	0.450
Log of household income	0.2040	0.010	0.000	0.0242	0.018	0.184
Has liquidity	0.0965	0.012	0.000	0.1005	0.020	0.000
Belgium	-0.4117	0.020	0.000	-..-	-..-	-..-
Spain	-0.2269	0.017	0.000	-..-	-..-	-..-
France	-0.2312	0.016	0.000	-..-	-..-	-..-
Italy	-0.2511	0.016	0.000	-..-	-..-	-..-
Netherlands	-0.3066	0.021	0.000	-..-	-..-	-..-
July wave	0.1144	0.008	0.000	0.1176	0.009	0.000
October wave	0.1679	0.008	0.000	0.1744	0.009	0.000
Constant	4.6382	0.100	0.000	6.7726	0.188	0.000
Number of observations		23,211			23,220	

Notes. Consumption is expressed in natural logarithms. Consumption and income are PPP-adjusted. Data are drawn from the April, July, and October waves of the CES.

Table 4. Concern about the household's financial situation due to Covid-19 and the MPC: results from Tobit and fixed effects OLS models

Variable	Tobit			Fixed effects OLS		
	Coeff.	Std. Error	p-value	Coeff.	Std. Error	p-value
	Panel A. MPC-					
Concern due to Covid-19 about the household's financial situation	0.0050	0.001	0.000	-..-	-..-	-..-
Number of observations	8,343			-..-		
	Panel B. MPS-					
Concern due to Covid-19 about the household's financial situation	0.0041	0.001	0.000	-..-	-..-	-..-
Number of observations	8,342			-..-		
	Panel C. MPC+					
Concern due to Covid-19 about the household's financial situation	0.0000	0.001	0.996	0.0002	0.001	0.861
Number of observations	15,506			15,510		
	Panel D. MPS+					
Concern due to Covid-19 about the household's financial situation	-0.0013	0.003	0.000	-0.0042	0.000	0.000
Number of observations	15,506			15,510		

Note. The table reports the marginal effect (in the case of Tobit) and coefficient (in the case of fixed effects OLS) of the variable denoting concern about the household's financial situation due to Covid-19. MPC- and MPS- denote the marginal propensities to consume on non-durables, and on the sum of non-durables, respectively, out of negative income shocks. MPC+ and MPS+ denote the corresponding marginal propensities to consume out of positive income shocks. In the case of negative income shocks, the table reports cross-sectional Tobit regressions, while in the case of positive shocks the table reports Tobit with random effects. Full estimates are reported in the Appendix. Data are drawn from the May wave of the CES for the MPCs out of a negative income shock, May, and June waves for the MPCs out of a positive income shock.

Table 5. Concern about the household's financial situation due to Covid-19 and consumption: partial identification results

Assumptions	Lower bound	Upper bound	Lower Bound Low 95% CI	Lower Bound Upper 95% CI	Upper Bound Low 95% CI	Upper Bound Upper 95% CI
Exogenous treatment selection	-0.1191		-0.1462		-0.0929	
No assumptions	-4.5988	4.3019	-4.6700	-4.5306	4.2307	4.3701
MTR	-4.5988	0.0000	-4.6700	-4.5306	0.0000	0.0000
MTR + MIV	-4.1596	-0.0277	-4.2668	-4.0587	-0.0459	-0.0259
MTR + MIV + BV20	-0.1009	-0.0277	-0.1048	-0.0818	-0.0459	-0.0259
MTR + MIV + BV25	-0.1332	-0.0277	-0.1372	-0.1137	-0.0459	-0.0259
MTR + MIV + BV30	-0.1651	-0.0277	-0.1694	-0.1451	-0.0459	-0.0259
Number of observations			23,370			

Note. Consumption is expressed in natural logarithms. Magnitudes refer to the average treatment effect of a change in the concern about the household's financial situation due to Covid-19 from below to above the median level. Data are drawn from the April, July, and October waves of the CES.

Table 6. Concern about the household's financial situation due to Covid-19 and the MPC: partial identification results

Assumptions	Lower bound	Upper bound	Lower Bound Low 95% CI	Lower Bound Upper 95% CI	Upper Bound Low 95% CI	Upper Bound Upper 95% CI
	Panel A. MPC-					
Exogenous treatment selection	0.0425		0.0257		0.0593	
No assumptions	-0.4781	0.5219	-0.4902	-0.4663	0.5098	0.5337
MTR	0.0000	0.5219	0.0000	0.0000	0.5098	0.5337
MTR + MIV	0.0193	0.5213	0.0173	0.0329	0.5052	0.5218
MTR + MIV + BV35	0.0193	0.0742	0.0173	0.0329	0.0608	0.0775
MTR + MIV + BV40	0.0193	0.0877	0.0173	0.0329	0.0740	0.0914
MTR + MIV + BV45	0.0193	0.1011	0.0173	0.0329	0.0874	0.1053
Number of observations			8,363			
	Panel B. MPS-					
Exogenous treatment selection	0.0506		0.0282		0.0738	
No assumptions	-0.4750	0.5257	-0.4863	-0.4634	0.5144	0.5373
MTR	0.0000	0.5257	0.0000	0.0000	0.5144	0.5373
MTR + MIV	0.0311	0.5202	0.0268	0.0527	0.5029	0.5239
MTR + MIV + BV40	0.0311	0.1222	0.0268	0.0527	0.1021	0.1262
MTR + MIV + BV45	0.0311	0.1409	0.0268	0.0527	0.1209	0.1448
MTR + MIV + BV50	0.0311	0.1596	0.0268	0.0527	0.1397	0.1635
Number of observations			8,362			
	Panel C. MPC+					
Exogenous treatment selection	-0.0050		-0.0076		0.0173	
No assumptions	-0.4857	0.5143	-0.4957	-0.4757	0.5043	0.5243
MTR	-0.4857	0.0000	-0.4957	-0.4757	0.0000	0.0000
MTR + MIV	-0.4375	-0.0127	-0.4596	-0.4155	-0.0217	-0.0102
MTR + MIV + BV30	-0.0569	-0.0127	-0.0630	-0.0467	-0.0217	-0.0102
MTR + MIV + BV35	-0.0685	-0.0127	-0.0751	-0.0578	-0.0217	-0.0102
MTR + MIV + BV40	-0.0799	-0.0127	-0.0875	-0.0688	-0.0217	-0.0102
Number of observations			15,545			
	Panel D. MPS+					
Exogenous treatment selection	-0.0277		-0.0456		-0.0102	
No assumptions	-0.6712	0.6621	-0.6819	-0.6606	0.6514	0.6727
MTR	-0.6712	0.0000	-0.6819	-0.6606	0.0000	0.0000
MTR + MIV	-0.6179	-0.0104	-0.6451	-0.5912	-0.0219	-0.0102
MTR + MIV + BV20	-0.0610	-0.0104	-0.0633	-0.0486	-0.0219	-0.0102
MTR + MIV + BV25	-0.0789	-0.0104	-0.0819	-0.0663	-0.0219	-0.0102
MTR + MIV + BV30	-0.0969	-0.0104	-0.1005	-0.0841	-0.0219	-0.0102
Number of observations			15,545			

Note. Magnitudes refer to the average treatment effect of a change in the concern about the household's financial situation due to Covid-19 from below to above the median level. MPC- and MPS- denote the marginal propensities to consume on non-durables, and on the sum of non-durables, respectively, out of negative income shocks. MPC+ and MPS+ denote the corresponding marginal propensities to consume out of positive income shocks. Data are drawn from the May and June waves of the CES.

Appendix

A. Partial identification[5]

A.1. Bounds on potential outcomes

As in Manski (1997), let every individual i have a response function $y_i(\bullet): D \rightarrow Y$ that maps mutually exclusive and exhaustive treatments $d \in D$ into outcomes $y_i(d) \in Y$. Importantly, the response functions $y_i(\bullet)$ can differ across individuals in arbitrary ways, thus allowing for unlimited response heterogeneity. Let w_i denote the realized treatment received by i, and $y_i \equiv y_i(w_i)$ the associated observed outcome. In our case, the outcomes are the logarithm of spending on non-durables and the various MPCs, while the treatment variable is the Covid-19 financial concern and is a binary variable, denoting concern at the median or below and above the median.

Let $y_i(d_1)$ and $y_i(d_2)$ be two possible values of the outcome for individual i as a function of two different levels of consumption uncertainty d_1 and d_2, with $d_2 > d_1$. We would like to estimate the ATE of increased Covid-19 financial concern on our outcomes, that is,

$$ATE(d_2 - d_1) = E[y(d_2)] - E[y(d_1)] \qquad \text{(A.1)}$$

Note that the ATE in (A.1) represents the difference in the two mean outcomes, which are both evaluated using all population units while taking the distribution of all other observable and unobservable variables as given (Manski 1997, p. 1322). By the law of iterated expectations, and given that $E[y(d)|w = d] = E(y|w = d)$, the expected outcome, when the treatment is equal to d, is

$$E[y(d)] = E(y|w = d)P(w = d) + E[y(d)|w \neq d]P(w \neq d) \qquad \text{(A.2)}$$

where $P(w = d)$ denotes the probability that $w = d$. Note that the term $E[y(d)|w \neq d]$ on the right-hand side of (A.2) is an unobserved counterfactual one. The remaining three terms on the right-hand side of (A.2), however, have sample analogues that are observed in the data. Given that $E[y(d)|w \neq d]$ is unobserved, the unconditional expectation $E[y(d)]$ is also unobserved. Hence the ATE in (1) is equal to the difference between two average unobserved outcomes, and thus cannot be calculated without further assumptions.

[5] This Appendix draws from Christelis et al. (2020), and Christelis and Dobrescu (2020).

If one assumes that the counterfactual conditional expectation $E[y(d)|w \neq d]$ is equal to the observed one when the treatment received is equal to d, that is, if

$$E[y(d)|w \neq d] = E(y|w = d) \tag{A.3}$$

then from (A.2) it follows that

$$E[y(d)] = E(y|w = d) \tag{A.4}$$

Equation (A.4) states that the unobserved potential outcome under d is equal to the mean outcome when the treatment in fact received is d. As the sample analogue of the latter is observed in the data, one can estimate the unobserved potential outcome $E[y(d)]$, and then the ATE from equation (A.4) as

$$ATE(d_2 - d_1) = E(y|w = d_2) - E(y|w = d_1) \tag{A.5}$$

We refer to the ATE estimate in (A.5) as the one under exogenous treatment selection (ETS henceforth) because it is derived under the assumption that (A.3) holds, which in turn implies that respondents receiving different treatments are not systematically different from one another. In other words, (A.3) implies that selection into treatment is exogenous.

Equation (A.3) is likely to hold in the case of a randomized control trial, in which treatment assignment is indeed exogenous. In observational data, however, (A.3) is unlikely to hold because treatment assignment is typically not random. In our context, the Covid-19 financial concern might be affected by unobservable variables that also affect spending. Hence, spending is likely to differ among population groups defined by different levels of Covid-19 financial concern, and this holds for any value d of this concern.

Once one rules out the application of (A.3), the problem of estimating the unobservable potential outcome $E[y(d)]$ arises. As a solution, Manski (1990) suggested bounding this outcome from above and below by bounding the counterfactual potential outcome $E[y(d)|w \neq d]$ in (A.2). Let us denote the lower and upper bounds on $E[y(d)]$, computed using a set of assumptions M, as $LB^M(d)$ and $UB^M(d)$, respectively. Given that $LB^M(d) \leq E[y(d)] \leq UB^M(d)$, Manski (1990) points out that equation (A.1) in turn implies that one can bound the ATE using a set of assumptions M as follows:

$$LB^{M}(d_2) - UB^{M}(d_1) \leq ATE(d_2 - d_1) \leq UB^{M}(d_2) - LB^{M}(d_1) \qquad \text{(A.6)}$$

The interval between the lower and the upper bound on the $ATE(d_2 - d_1)$ (which are denoted by $LB^{M}_{ATE}(d_2 - d_1)$ and $UB^{M}_{ATE}ATE(d_2 - d_1)$, respectively) is its identification region. Since it is an interval, the ATE is only partially identified.

A.2. Bounds using no assumptions

When calculating the upper and lower bounds on $E[y(d)]$, a natural starting point is to assume that, for any value d of the treatment, the outcome space Y is bounded below and above by two finite values, Y_{min} and Y_{max}, respectively. These values can be used to bound $E[y(d)|w \neq d]$. In our context, we use as Y_{min} and Y_{max} the minimum and maximum the observed distribution of the winsorized (at 0.5 and 99.5 percent) distribution of spending, respectively. For the MPCs, Y_{min} is equal to 0 and Y_{max} is equal to 1.

Given that Y_{min} and Y_{max} are very conservative bounds on $E[y(d)|w \neq d]$, we consider the resulting identification regions of $E[y(d)]$ and the ATE as ones derived under no assumptions (NA henceforth).

As in Manski (1990), one can replace the counterfactual term $E[y(d)|w \neq d]$ in (A.2) by Y_{min} and Y_{max}, and thus bound $E[y(d)]$ from below and above as follows:

$$\begin{gathered} E(y|w = d)P(w = d) + Y_{min}\, P(w \neq d) \\ \leq E[y(d)] \leq \\ E(y|w = d)P(w = d) + Y_{max}P(w \neq d) \end{gathered} \qquad \text{(A.7)}$$

The bounds in (A.7) are obtained without imposing any assumptions on the data, other than the existence of finite Y_{min} and Y_{max} The NA bounds can be readily calculated using their sample analogues, as these are observed in the data. As Manski (1989) points out, taking sample averages leads to consistent estimates of $E(y|w = d)$, $P(w = d)$ and $P(w \neq d)$.

A.3. The MTR assumption

The NA identification regions are typically very wide, and thus uninformative (they always include zero), as one would expect when using weak assumptions. It is possible, however, to narrow the NA identification region by making further assumptions. The first such assumption is that of monotone treatment response (MTR henceforth; see Manski, 1997). In our context, the MTR assumption implies that the Covid-19 financial concern has a weakly negative effect on actual spending, MPC+ and MPS+, and a weakly positive effect on MPC- and MPS+ (that is, it makes the consumption drop larger). We discuss here the first case, that is, of a weakly negative effect (results for a weakly positive effect are completely analogous).

In the case of a weakly negative treatment response, the MTR assumption states that for all sample units i, and for any two treatment values $d_1 \in D$ and $d_2 \in D$ such that $d_2 > d_1$,

$$y_i(d_2) \leq y_i(d_1) \tag{A.8}$$

Importantly, (A.8) holds irrespective of the treatment actually received, and for all households in the sample. Given that at each point in time one observes only one outcome for every household in the sample, one cannot test for the validity of (A.8) in isolation using the data at hand. As already discussed, however, there are various reasons, also supported by considerable evidence, why one would expect the Covid-19 financial concern to have a weakly negative effect on spending, most obviously precautionary saving.

In practice, we use a weaker, and thus more conservative, version of the MTR assumption than the one in (A.8). This weaker version states that for any treatment value $d \in D$, and any two values $d_1 \in D$ and $d_2 \in D$ such that $d_2 > d_1$,

$$E[y(d_2)|w = d] \leq E[y(d_1)|w = d] \tag{A.9}$$

Equation (A.9) implies that consumption uncertainty has a weakly negative effect on spending on average, that is, not necessarily for every household in the sample. Furthermore, this average weak monotonicity holds for all subsamples that are defined by the treatment in fact received.[6] Clearly, (A.8) implies (A.9), but the converse is not necessarily true.

[6] Given that (A11) holds for all values d of the observed treatment w, it is clearly the case that the weak monotonicity in (A11) applies also to the unconditional expectation, i.e., (A11) implies that $E[y(d_2)] \leq E[y(d_1)]$. However, the converse need not be true.

Following the reasoning in Manski (1997) for the case of a weakly negative treatment response, the MTR assumptions (A.8) and (A.9) imply that the bounds on $E[y(d)]$ can be expressed as follows:

$$\begin{gathered} Y_{min}P(w < d) + E(y|w = d)P(w = d) + E(y|w > d)\, P(w > d) \\ \leq E[y(d)] \leq \\ E(y|w < d)P(w < d) + E(y|w = d)P(w = d) + Y_{max}P(w > d) \end{gathered} \quad \text{(A.10)}$$

This is so because under both (A.8) and (A.9) imply that $E(y|w > d)$ can be used as a lower bound for $E[y(d)|w > d]$ instead of Y_{min}. Similarly, both (A.8) and (A.9) imply that $E(y|w < d)$ can be used an upper bound for $E[y(d)|w < d]$ instead of Y_{max}. Given that $E(y|w > d)$ is likely considerably larger than Y_{min} and $E(y|w < d)$ considerably smaller than Y_{max}, the identification region defined in (A.10) should be considerably narrower, and thus more informative, than the one in (A.7) generated using no assumptions.

The above also imply that to obtain (A.10) one can use the weaker assumption (A.9) that states that MTR holds only on average for each subgroup defined by the treatment actually received instead of the stronger assumption (A.8) that states that MTR holds for every sample unit.

Importantly, Manski (1997) shows that in the case of a weakly increasing MTR the identification region of the ATE under MTR has a lower bound equal to zero because MTR rules out the possibility that a higher value of the treatment induces a lower mean outcome, while allowing for the possibility of a zero effect. In the case of a weakly decreasing MTR (as in our context), the corresponding result is that the MTR upper bound is equal to zero.

A particularly interesting instance of this result when examining the ATE of the change in the treatment from its minimum to its maximum value, denoted by d_{min} and d_{max}, respectively. Noting that $P(w < d_{min}) = P(w > d_{max}) = 0$ $P(w \geq d_{min}) = P(w \leq d_{max}) = 1$, the MTR bounds in (A.10) imply that $UB^{MTR}(d_{max}) = LB^{MTR}(d_{min}) = E(y)$. In other words, the MTR assumption leads to the replacement of all counterfactual terms in $UB^{MTR}(d_{max})$ and $LB^{MTR}(d_{max})$ with observed outcomes, and both these bounds become equal to the observed overall mean. This in turn implies that $UB_{ATE}^{MTR}(d_{max} - d_{min}) = UB^{MTR}(d_{max}) - LB^{MTR}(d_{min}) = 0$.

Clearly, this result applies to our context as well because we have a binary treatment, and thus $d_1 = d_{min}$ and $d_2 = d_{max}$.

A.4. The bounded variation assumption

The MTR assumption cannot provide a lower bound for the counterfactual term $E[y(d)|w < d]$ nor an upper bound for the counterfactual term $E[y(d)|w > d]$. However, instead of using Y_{min}, one can provide bounds for the former term by assuming that its lower bound cannot be smaller than the observed term $E(y|w < d)$ reduced by a given amount, which we assume to be equal to a multiple k of the standard deviation of the outcome $SD(y)$. Hence, we have

$$E(y|w < d) - kSD(y) \leq E[y(d)|w < d] \leq E(y|w < d) \quad \text{(A.11)}$$

(A.11) also implies that $0 \leq E(y|w < d) - E[y(d)|w < d] \leq kSD(y)$. In other words, (A.11) implies that for the subsample defined by $w < d$ there is a bound, equal to $kSD(y)$, on how large the effect of the MTR assumption is.

Correspondingly, instead of using Y_{max}, one can provide an upper bound for the counterfactual term $E[y(d)|w > d]$ by assuming that this upper bound cannot be larger than the observed term $E(y|w > d)$ augmented by a given amount, which we assume to be equal to a multiple k of the standard deviation of the outcome $SD(y)$. Hence, we have

$$E(y|w > d) \leq E[y(d)|w > d] \leq E(y|w > d) + kSD(y) \quad \text{(A.12)}$$

(A.12) also implies that $0 \leq E[y(d)|w > d] - E(y|w > d) \leq kSD(y)$. In other words, (A.12) implies that for the subsample defined by $w > d$ there is a bound, equal to $kSD(y)$, on how large the effect of the MTR assumption is.

These assumptions are examples of the bounded variation (BV) assumption discussed in Manski and Pepper (2018). There are no clear-cut criteria dictating the choice of the multiple k of $SD(y)$, other than the necessity to avoid the crossing of the bounds on $E(y)$ as well as those on the ATE. Crossing of the bounds could indicate in different circumstances that assumptions can generate identification regions that are so tight as to lead to point identification. However, this presupposes that there are good reasons to use those assumptions, and such reasons are not easy to find for a particular value of the multiple k that makes the bounds cross.

Combining (A.11) and (A.12) we have

$$\begin{gathered}[E(y|w<d)-kSD(y)]P(w<d)+E(y|w\geq d)P(w\geq d)\\ \leq E[y(d)]\leq \\ E(y|w\leq d)P(w\leq d)+[E(y|w>d)+kSD(y)]P(w>d)\end{gathered} \tag{A.13}$$

When examining the $ATE(d_{max}-d_{min})$, and since $P(w<d_{min})=P(w>d_{max})=0$ and $P(w\geq d_{min})=P(w\leq d_{max})=1$, we again have, as was the case when using only MTR that $UB^{MTR+BVk}(d_{max})=LB^{MTR+BVk}(d_{min})=E(y)$, and thus $UB_{ATE}^{MTR+BVk}(d_{max}-d_{min})=UB^{MTR+BVk}(d_{max})-LB^{MTR+BVk}(d_{min})=0$. On the other hand, (A.13) implies that $LB^{MTR+BVk}(d_{max})=[E(y|w<d_{max})-kSD(y)]P(w<d_{max})+E(y|w=d_{max})P(w=d_{max})$, while we have $UB^{MTR+BVk}(d_{min})=E(y|w=d_{min})P(w=d_{min})+[E(y|w>d_{min})+kSD(y)]P(w>d_{min})$. Hence, the identification region of the $ATE(d_{max}-d_{min})$ under MTR+BVk becomes

$$\begin{gathered}\{[E(y|w<d_{max})-kSD(y)]P(w<d_{max})\\ +E(y|w=d_{max})P(w=d_{max})\}-\\ \{E(y|w=d_{min})P(w=d_{min})\\ +[E(y|w>d_{min})+kSD(y)]P(w>d_{min})\}\\ \leq ATE(d_{max}-d_{min})\leq\\ 0\end{gathered} \tag{A.14}$$

In our context, given that $d_1=d_{min}$ and $d_2=d_{max}$, and that $E(y|w<d_2)=E(y|w=d_1)$, $E(y|w>d_1)=E(y|w=d_2)$, $P(w<d_2)=P(w=d_1)$, $P(w>d_1)=P(w=d_2)$, the lower bound of the $ATE(d_{max}-d_{min})=ATE(d_2-d_1)$ in (A.14) becomes equal to $-kSD(y)P(w=d_1)-kSD(y)P(w=d_2)=-kSD(y)$, and thus we get

$$-kSD(y)\leq ATE(d_2-d_1)\leq 0 \tag{A.14a}$$

A.5. The MIV assumption

One can further narrow the identification region of the ATE by using a considerably weaker kind of IV than the usual exogenous one, namely the MIV. MIVs were introduced by Manski and Pepper (2000), and they satisfy the following requirement for any pair of values z_1, z_2 of Z such that $z_2 > z_1$,

$$E[y(d)|Z = z_2, X] \geq E[y(d)|Z = z_1, X] \tag{A.15}$$

where X are a set of control variables. Equation (A.15) states that the MIV can influence the outcome in a particular direction, but also allows for the possibility of no influence whatsoever. Hence, this requirement is much weaker than that of an exogenous instrument which requires no direct relationship between the instrument and the outcome. It is important to note that (A.15) captures only a positive association of Z with Y; a causal relationship is neither implied nor required.

To better understand how MIVs work, we first note that we can always express the lower bound on $E[y(d)]$ under a set of assumptions M as

$$LB^M(d) = \sum_X \sum_z LB^M(d|Z = z, X)\, P(Z = z|X)P(X) \tag{A.16}$$

Clearly, $P(Z = z|X)$ and $P(X)$ are given in the data and thus cannot be changed. Hence, the unconditional lower bound $LB^M(d)$ can increase only by increasing the conditional lower bounds $LB^M(d|Z = z, X)$. Similarly, to decrease the unconditional upper bound $UB^M(d)$ one must decrease the conditional upper bounds $UB^M(d|Z = z, X)$.

Let us first examine how an exogenous IV (XIV) – the IV type typically used in treatment effect estimation - can help narrow the identification range. Following Manski (1990), a variable Z is a XIV if $\forall\ d \in D, \forall\ z \in Z$,

$$E[y(d)|\ Z = z, X] = E[y(d)|X] \tag{A.17}$$

Equation (A.17) implies that conditioning on any value of the XIV does not change the mean potential outcome. Hence, all identification regions conditional on values of Z should provide identical lower and upper bounds on $E[y(d)|X]$. Therefore, the identification region of $E[y(d)|X]$ is the intersection of all identification regions conditional on Z. This intersection is contained between the maximum of all conditional lower bounds and the minimum of all conditional upper bounds. Hence, we have

$$\max_z LB^M(d|Z=z,X) \leq E[y(d)|X] \leq \min_z UB^M(d|Z=z,X) \qquad \text{(A.18)}$$

Hence, using XIVs implies that one searches for the maximum lower bound and the minimum upper bound on $E[y(d)|X]$ by partitioning the subsample conditional on X in cells defined by the XIV values and then comparing the extrema calculated in each cell. This search for the extrema is analogous to the search for extrema of objective functions in a dynamic program, or of likelihood functions in econometric estimation, which occurs in subsets of the parameter space defined by the chosen grid and/or the optimization method. Clearly, different XIVs will define different partitions of the sample space, and thus likely yield different extrema.

There are, however, a couple of key difference between searching for extrema in the sample space versus the parameter space: i) the size of the sample partitions is in practice constrained by the number of observations in each cell, whereas there is no such constraint when partitioning the parameter space; and ii) local extrema of the bounds on $E[y(d)|X]$ define perfectly valid identification regions, similarly to less informative bounds computed using weaker assumptions. In other words, using different valid XIVs and various possible combinations of their values will always produce valid identification regions, albeit not necessarily the most informative ones. In contrast, local extrema of objective functions in a dynamic program or likelihood functions will typically yield estimates that are inconsistent and thus potentially misleading. Hence, PI optimization delivers considerably more robust results than dynamic programming or likelihood optimization.

When using an MIV, equation (A.17) does not hold because (A.15) implies that the MIV is weakly monotonically correlated with the outcome. As a result, one cannot calculate the overall identification region as the intersection of all conditional identification regions, as was the case with XIVs. On the other hand, it is possible to exploit the fact that, by (A.15), a lower bound on $E[y(d)|\, Z=z_1,X]$ is also a lower bound on $E[y(d)|\, Z=z,X]$ for $z \geq z_1$, and, correspondingly, an upper bound on $E[y(d)|\, Z=z_2,X]$ is also a upper bound on $E[y(d)|\, Z=z,X]$ for $z \leq z_2$. Hence, one can potentially increase the lower bound $LB^M(d|Z=z,X)$ in (A.16) by using the maximum lower bound $LB^M(d|Z=z_1,X)$ over all $z_1 \leq z$. Correspondingly, one can potentially decrease the upper bound $UB^M(d|Z = z, X)$ by using the minimum upper bound $UB^M(d|Z = z_2, X)$ over all $z_2 \geq z$. Hence, we obtain

$$\max_{z_1 \leq z} LB^M[d|Z = z_1, X] \leq E[y(d)|Z = z, X] \leq \min_{z \leq z_2} UB^M[d|Z = z_2, X] \qquad \text{(A.19)}$$

Once the bounds in (A.19) have been computed for all z, one can take their weighted average over all z and bound the potential outcome $E[Y(d)]$ as follows:

$$\begin{aligned} &\sum_X \sum_z \max_{z_1 \leq z} LB^M[d|Z = z_1, X]\, P(Z = z|X)P(X) \\ \leq &\sum_X \sum_z E[y(d)|Z = z, X]P(Z = z|X)P(X) = E[y(d)] \leq \qquad \text{(A.20)} \\ &\sum_X \sum_z \min_{z \leq z_2} UB^M[d|Z = z_2, X]\, P(Z = z|X)P(X) \end{aligned}$$

Hence, by integrating Z and X out of the bounds on the conditional expectation $E[y(d)|Z = z, X]$, one can obtain bounds on $E[y(d)]$.

Clearly, the optimization operations in (A.19) take place over a restricted range of values of Z compared to (A.18), and thus the identifying power of the MIV assumption is smaller than that of the XIV one. This is to be expected, as the weak monotonicity of a MIV in (A.15) is a weaker assumption than the exogeneity of an XIV in (A.17). As with XIVs, this weak monotonicity assumption is imposed on the unobserved potential outcome $E[y(d)|X]$; hence, it cannot be tested using the observed data without imposing further assumptions.

As is the case with XIVs, valid MIVs generate valid identification regions, although not necessarily the most informative ones.

In our context, the MIV used, namely age, is assumed to have a weakly positive effect on spending, the MPCs and the MPSs, conditional on income, as described in Section 6.1.

A.6 Advantages of PI

All in all, there are many reasons why one would prefer PI methods to other more commonly used ones (e.g. OLS-, IV- or panel data-based) when trying to estimate the causal effect of interest. First, PI methods are completely nonparametric, as they require only the calculation of sample averages of the outcome and the prevalence of the treatment.

Second, PI methods produce estimates of the ATE across all sample units, and not of the LATE as is the case with IV estimation when the treatment is heterogeneous. Thus, they allow for arbitrary forms of heterogeneity of the treatment effect because the ATE is just an average magnitude across sample units. Such unlimited heterogeneity of the treatment effect is not typically allowed for, as in most estimation methods one makes specific assumptions about how the treatment variable enters the specification. Moreover, if one is interested in the heterogeneity of the treatment effect in specific dimensions, then one can simply apply PI methods to subsamples defined by particular combinations of values of control variables.

Third, in PI one bounds the unconditional expectation $E[y(d)]$, taking as given the distribution of all observables and unobservables (other than the treatment) that might affect the outcome. Hence, one does not need to worry about i) which variables to add in the empirical specification; ii) the way they appear; and iii) whether they are endogenous.

Fourth, PI methods accommodate any form of endogeneity (e.g., due to both time-varying and time-invariant unobservables or selectivity), as they allow for any form of non-random selection into treatment. This also implies that one does not need to assume specific properties of the error term, as is the case with regression methods.

Fifth, PI uses very few and quite mild assumptions to narrow the identification region of the estimates. Importantly, it is completely transparent about how adding each assumption affects the identification region. In contrast, most commonly used estimation methods impose simultaneously many assumptions on the empirical model, and thus it is typically unclear how each of them affects estimates.

Sixth, PI methods allow the use MIVs that can tighten the identification regions. As is the case with standard IV estimation, the assumptions behind those variables cannot be tested without making further assumptions. However, MIVs - unusable in standard IV estimation - are required to be weakly monotonically related to the outcome, which is a much weaker assumption than the exogeneity required of standard IVs.

Seventh, PI can operate without problems on cross-sectional data, and so panel data are not required. This is so because PI assumes that the treatment is endogenous, and this endogeneity can be due to time-varying or time-invariant unobservables, or both. One can accommodate dependencies among sample units (e.g. due to repeated observation or features of the sampling process) through the appropriate clustering and stratification when bootstrapping standard errors.

Appendix References

Christelis, Dimitris, and Loretti I. Dobrescu (2020), "The causal effect of social activities on cognition: Evidence from 20 European countries," *Social Science and Medicine* 247, Article 112783.

Manski, Charles F. (1989), "Anatomy of the selection problem," *Journal of Human Resources* 24, 343–60.

Manski, Charles F. (1990), "Nonparametric Bounds on Treatment Effects," *American Economic Review Papers and Proceedings*, 80, 319-323.

Manski, Charles F. (1994), "The Selection Problem," in *Advances in Econometrics: Sixth World Congress*, ed. by C. Sims. Cambridge, UK: Cambridge University Press, 143–170.

Manski, Charles F. (1997), "Monotone Treatment Response," *Econometrica*, 65, 1311-1334.

Manski, Charles F. , and John V. Pepper (2000), "Monotone Instrumental Variables, with an Application to the Returns to Schooling," *Econometrica* 68, 997-1012.

Manski, Charles F., and John V. Pepper (2018), "How Do Right-to-Carry Laws Affect Crime Rates? Coping with Ambiguity Using Bounded Variation Assumptions," *Review of Economics and Statistics* 100, 232–244.

Table A1. Determinants of the concern about own and household members' health due to Covid-19

Variable	OLS			Ordered probit		
	Coeff.	Std. Error	p-value	Coeff.	Std. Error	p-value
Age 36-59	0.102	0.049	0.035	0.057	0.020	0.005
Age 60+	0.135	0.067	0.045	0.065	0.028	0.020
Household size	0.081	0.017	0.000	0.034	0.007	0.000
Male financial respondent	-0.328	0.042	0.000	-0.141	0.017	0.000
Secondary education	-0.065	0.065	0.313	-0.033	0.028	0.247
Tertiary education	-0.155	0.060	0.010	-0.073	0.027	0.006
Employed full-time	-0.058	0.064	0.360	-0.013	0.026	0.614
Employed part-time or on extended leave	-0.022	0.067	0.742	0.011	0.028	0.701
Unemployed	-0.030	0.075	0.685	0.009	0.032	0.778
Log of household income	-0.055	0.031	0.075	-0.030	0.013	0.019
Has liquidity	-0.302	0.042	0.000	-0.151	0.018	0.000
Belgium	0.524	0.083	0.000	0.209	0.033	0.000
Spain	1.957	0.066	0.000	0.882	0.029	0.000
France	0.538	0.066	0.000	0.211	0.026	0.000
Italy	0.425	0.070	0.000	0.173	0.027	0.000
Netherlands	-0.178	0.083	0.032	-0.087	0.031	0.005
May wave	-0.382	0.028	0.000	-0.165	0.012	0.000
June wave	-0.649	0.032	0.000	-0.277	0.014	0.000
July wave	-0.637	0.032	0.000	-0.276	0.013	0.000
October wave	-0.344	0.032	0.000	-0.153	0.014	0.000
Constant	7.179	0.319	0.000	-..-	-..-	-..-
Number of observations				39,810		

Notes. OLS and ordered probit coefficients shown. Data are drawn from the April, July, and October waves of the CES.

Table A2. MPC on non-durables from positive income shocks in the 2017 HFCS and 2020 CES surveys

Country	2020 CES	2017 HFCS
Belgium	35.8	42.0
Germany	48.0	51.3
France	45.2	41.8
Italy	38.9	48.1
Netherlands	33.1	32.9
Spain	37.3	n.a.

Notes: The table shows reported marginal propensities to consume on non-durables out of positive income shocks in the 2020 CES and in the 2017 wave of the Household Finance and Consumption. Data are drawn from the May and June waves of the CES, and Drescher et al. (2020) for HFCS data.

Table A3. Concern about the household's financial situation due to Covid-19 and consumption out of a negative income shock: results from Tobit models

Variable	MPC-			MPS-		
	Coeff.	Std. Error	p-value	Coeff.	Std. Error	p-value
Concern due to Covid-19 about the household's financial situation	0.0050	0.0008	0.0000	0.0041	0.0007	0.0000
Concern about own and household member's health due to Covid-19	0.0007	0.0008	0.3747	0.0011	0.0007	0.1026
Age 36-59	-0.0052	0.0041	0.2002	-0.0010	0.0036	0.7831
Age 60+	-0.0012	0.0057	0.8308	0.0009	0.0050	0.8645
Household size	-0.0009	0.0014	0.5244	0.0013	0.0013	0.3023
Male financial respondent	-0.0060	0.0035	0.0803	0.0043	0.0030	0.1558
Secondary education	0.0045	0.0055	0.4120	0.0025	0.0048	0.5990
Tertiary education	0.0028	0.0052	0.5971	-0.0037	0.0046	0.4156
Employed full-time	0.0035	0.0056	0.5324	-0.0025	0.0049	0.6024
Employed part-time or on extended leave	0.0135	0.0060	0.0234	0.0089	0.0052	0.0869
Unemployed	-0.0002	0.0068	0.9760	-0.0014	0.0060	0.8179
Log of household income	-0.0075	0.0026	0.0034	-0.0032	0.0022	0.1581
Has liquidity	-0.0090	0.0039	0.0220	-0.0022	0.0035	0.5170
Belgium	0.0048	0.0064	0.4484	-0.0135	0.0056	0.0153
Spain	0.0087	0.0056	0.1210	-0.0086	0.0049	0.0783
France	-0.0040	0.0054	0.4574	-0.0212	0.0047	0.0000
Italy	-0.0050	0.0054	0.3576	0.0056	0.0047	0.2351
Netherlands	-0.0009	0.0067	0.8924	-0.0199	0.0058	0.0006
Number of observations		8,343			8,342	

Note. The table reports marginal effects, derived out of a Tobit model. MPC- and MPS- denote the marginal propensities to consume on non-durables, and on the sum of non-durables, respectively, out of positive income shocks. Data are drawn from the May wave of the CES.

Table A4. Concern about the household's financial situation due to Covid-19 and consumption out of a positive income shock: results from panel data rando effects Tobit and fixed effect OLS models

Variable	MPC+						MPS+					
	Random effects tobit			Fixed effects OLS			Random effects tobit			Fixed effects OLS		
	Coeff.	Std. Error	p-value	Coeff.	Std. Error	p-value	Coeff.	Std. Error	p-value	Coeff.	Std. Error	p-value
Concern due to Covid-19 about the household's financial situation	0.0000	0.0005	0.9955	0.0002	0.0009	0.8606	-0.0013	0.0005	0.0097	-0.0042	0.0014	0.0022
Concern about own and household member's health due to Covid-19	0.0018	0.0005	0.0008	0.0024	0.0009	0.0047	0.0010	0.0005	0.0485	0.0021	0.0013	0.1167
Age 36-59	-0.0076	0.0029	0.0076	-..-	-..-	-..-	-0.0013	0.0029	0.6458	-..-	-..-	-..-
Age 60+	-0.0096	0.0040	0.0157	-..-	-..-	-..-	0.0070	0.0040	0.0818	-..-	-..-	-..-
Household size	0.0002	0.0010	0.8061	-..-	-..-	-..-	0.0027	0.0010	0.0078	-..-	-..-	-..-
Male financial respondent	-0.0018	0.0024	0.4501	-..-	-..-	-..-	-0.0027	0.0024	0.2652	-..-	-..-	-..-
Secondary education	-0.0100	0.0039	0.0096	-..-	-..-	-..-	-0.0039	0.0039	0.3204	-..-	-..-	-..-
Tertiary education	-0.0104	0.0036	0.0042	-..-	-..-	-..-	-0.0029	0.0037	0.4304	-..-	-..-	-..-
Employed full-time	-0.0110	0.0039	0.0044	-..-	-..-	-..-	-0.0074	0.0039	0.0586	-..-	-..-	-..-
Employed part-time or on extended leave	-0.0051	0.0041	0.2196	-..-	-..-	-..-	0.0006	0.0042	0.8866	-..-	-..-	-..-
Unemployed	-0.0011	0.0047	0.8093	-..-	-..-	-..-	-0.0012	0.0048	0.8052	-..-	-..-	-..-
Log of household income	-0.0037	0.0019	0.0483	0.0002	0.0031	0.9513	0.0002	0.0018	0.9035	0.0108	0.0045	0.0174
Has liquidity	0.0122	0.0028	0.0000	0.0186	0.0047	0.0001	0.0233	0.0027	0.0000	0.0646	0.0071	0.0000
Belgium	-0.0206	0.0045	0.0000	-..-	-..-	-..-	-0.0401	0.0045	0.0000	-..-	-..-	-..-
Spain	-0.0093	0.0039	0.0186	-..-	-..-	-..-	-0.0324	0.0040	0.0000	-..-	-..-	-..-
France	-0.0045	0.0038	0.2322	-..-	-..-	-..-	-0.0043	0.0038	0.2647	-..-	-..-	-..-
Italy	-0.0131	0.0038	0.0006	-..-	-..-	-..-	-0.0227	0.0038	0.0000	-..-	-..-	-..-
Netherlands	-0.0451	0.0048	0.0000	-..-	-..-	-..-	-0.0495	0.0047	0.0000	-..-	-..-	-..-
Junewave	-0.0117	0.0023	0.0000	-0.0073	0.0035	0.0381	-0.0076	0.0018	0.0000	-0.0164	0.0049	0.0009
Number of observations	15,506			15,510			15,506			15,510		

Note. The table reports the marginal effects (in the case of a random effects Tobit) and coefficients (in the case of a fixed effects OLS model). MPC+ and MPS+ denote the marginal propensities to consume on non-durables, and on the sum of non-durables, respectively, out of positive income shocks. Data are drawn from the May and June waves of the CES.