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The effects of the 2020 lockdown on consumption and savings in Spain

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Abstract

This paper investigates the causal effect of the lockdown on different consumption items using data from the Spanish Household Budget Survey. Our analysis reveals that the lockdown induced effects on the intratemporal distribution of total expenditure. The decline in total expenditure masks different changes both in commodity groups and in the distribution of expenditure. Furthermore, these effects varied with different stages of the pandemic. Our findings also suggest that the lockdown measures, along with subsequent restrictions throughout 2020, engendered an unexpected and household-specific variation in savings rates. This, coupled with fluctuations in relative prices, could have influenced other economic dimensions such as inequality and welfare.

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1 Introduction

This paper is devoted to analyze the effect of the lockdown that took place during Spain's 2020 state of alarm -which was extraordinarily rigorous and severe in the Spanish case (Romero and Redondo, 2021)-, on the consumption of Spanish households. The effect of the lockdown has been studied from several angles, specially those concerning health. Solé *et al.* (2021) study the impact on mental health. Costa-Font *et al* (2021) analyze the drastic consequences on the Spanish population, especially for older adults living in nursing homes, during the first wave of the pandemic. A wide line of research deals with economic issues, either from a micro or macro perspective, given that mobility and consumption out of home were severely restricted due to the state of emergency. In this sense, we expect the lockdown to dramatically affect several consumption items specially in the short run, with some potential permanent long run effects too. Previous studies focused either on food consumption or credit card use. Navarro-Pérez *et al.* (2022) analyses dietary habits and Carvalho *et al.* (2021) study credit card consumption reduction using transaction data, both with Spanish data. At the international level, several papers dealt with food consumption. Some of them are Coibion *et al*, with a macroeconomic focus, Janssen *et al.* (2022) that analyze the cases of Denmark, Germany and Slovenia . Inmordino *et al.* (2021) study the effect of fear of COVID-19 contagion and income risk on consumption using a specifically-designed household survey of Italian households.

Our paper attempts to do a quantitative assessment of the lockdown effect on consumption expenditure in Spain using survey data. Some existing literature instead provides a qualitative analysis of the change in consumption habits based on surveys, such as Hotbod *et al.* (2021). On the quantitative side, Baker *et al.* (2021) use a panel of transaction-level household financial data from the US and find evidence of a spike in food and retail expenditure in the very short run with the effects varying according to family structure but not to income. The initial response of households previous to lockdown was an increase in spending due to stockpiling and anticipation effects. As the virus spread during March 2020 and more households stayed home, they detect sharp drops in restaurants, retail, air travel and public transport. Inmordino *et al.* (2021) provide evidence how household consumption drops while savings increase as a result of the fear of contracting the virus through different economic and social activities as working or shopping. Together with the economic circumstances potentially affecting decision-making, fear of contagion represents another factor that drives individual behavior, with relevant consequences for the effectiveness of public policies aiming at stimulating consumption.

In this paper we use data from the Spanish Household Budget Survey, the main survey collecting information on income, consumption and demographics in Spain. Although we have a long time period, this exercise only focuses on years 2018 to 2020 since we aim at estimating causal effects of the pandemic on the demand for several goods using data for 2019 and 2020, while providing robustness checks comparing the results with the households' behavior in 2018-2019. Although the data was collected during the whole 2020 and was made available in June 2021, we are lucky to have available the two-week period when the household was interviewed. This information is crucial because it allows us to identify our control and treatment groups and to observe time variation in prices. We can further exploit this feature to examine the different effects of the lockdown and post-lockdown on consumption of some items at the bi-week frequency.[1] We think the lockdown implied a changing-behaviour for some groups of the population as Inmordino *et al.* (2021) show and, then, the effects extended along 2020 and, probably, during the different waves of the pandemic up to the completion of the vaccination schedule.

Given the sharp and unanticipated nature of the lockdown we consider two complementary identification strategies: Differences in Differences (DiD) and Regression Discontinuity Design (RDD). The first one exploits the change in consumption of those consumers observed both in 2019 and in after the lockdown in 2020, serving as our treated group, while those observed in the same weeks of the two years, but before the lockdown in 2020, are used as controls. The second one compares consumption patterns just before and after the lockdown deadline. Both strategies are applied in a linear regression context and also, accounting for the fact that for many items observed consumption is zero, in a two part model context (see Pohlmeier and Ulrich, 1995; Santos-Silva and Windmeijer, 1999; and Jones, 1989 for consumption models) with possible correlation between the two parts. We try to test changes in consumption patterns, but also whether non-consumers (consumers) before COVID-19 change their regime as a consequence of the lockdown.

We detect, on average, a sharp drop in consumption (around -10% in-6% in our baseline DiD and RDD specifications, respectively). The negative effect is observed in a large majority of products or groups of products (clothing, transportation, Tobacco, consumption outside home,etc). Yet we observe important positive increases in aggregate food consumption, with prominent effects on luxury food items (for example lamb and seafood). These changes have a direct impact on the average household savings rate, with a positive increase of between 5 and 10 basis points.

[1]We look at the bi-weekly effects after the arrival of COVID-19 because we only have two annual observations per household and thus we cannot do an event study of the effects once the lockdown took place.

The structure of the rest of the paper is as follows. Section 2 describes the data. The identification strategy, empirical model and the main results from the analysis can be found in section 3. Section 4 explores the variation of the results to changes in the definition of the sample as well as the heterogeneity by age and income. Section 5 reports several robustness checks to ensure that we really estimate causal effects of the lockdown. Section 6 explores the implication of the previous results for savings and future consumption. Finally, section 5 concludes.

2 Data description

2.1 The data source

We use data from the Spanish Household Budget Survey (Encuesta de Presupuestos Familiares, EPF) conducted by the Spanish National Institute of Statistics (INE). The current format of the EPF at the time of doing this research covered the period 2006-2021. The survey follows a household for a maximum of two years with sample size about 22,000 households per year. Information is mainly provided by members of each household keeping a diary record of what they spend over two weeks. They are asked to provide expenditure at daily, weekly, monthly, quarterly, or annual frequencies, but all the data is reported on an annual basis. We are able to pinpoint the exact two-week period when the household was interviewed. This is important to identify our control and treatment groups as well as to allow for time variation in prices. The EPF collects information on households' expenditures on 479 different goods and services as well as a wide range of socio-demographic information. It constitutes the main source of microdata on spending behavior by Spanish households and it is used to compute the weights for the official Retail Price Index (RPI), as well as the national income accounting aggregate for private consumption.

Although the data covers the period 2006-2021, the survey and the computation of the RPI suffered some changes in 2016 (see INE, 2016). The survey serves to annually update the weights of the components of the basket of goods. Because of the lockdown, the INE could not take prices of items; moreover, some goods and services were not available to consumers. This posed a challenge when computing the RPI during some months in 2020. The INE as well as most of the EU countries adapted both prices and weights to take care of this situation.[2]. The acknowledgement of the INE that the effects of the lockdown on the measurement of price evolution are relevant also implied academic reactions. Cavallo (2020) estimated the effects of the lockdown on inflation in Spain using data on card transactions. Evald *et*

[2]Details about the measures adopted, goods affected, weights adjusted and comparison of prices are in https://www.ine.es.

al. (2022) adjust these effects with data from the EPF by comparing the evolution of the index computed by the INE with a plutocratic price index computed using observed weights in the survey.[3] Once they calculate the difference, they also study its impact on inequality.

For the purposes of this paper, we use information for the period 2017-2020, and although we only have different prices for 122 goods, we can match them with the goods we study using the adequate weights. Now, we take a closer look to the evolution of some types of household expenditure over the 2017-2020 period. Particularly, we focus on how expenditure in some categories evolved each quarter of the sample period. Once differences are detected, we present very preliminary evidence of the lockdown effects on consumption using both DiD and a RDD. We rely on 2018 data to be able to compare these estimates to those of a *placebo treatment* defined identically as the original treatment, but one year before, i.e., when the event had not yet occurred.

2.2 Consumption evolution during 2018-2020

In this subsection we focus on how expenditure for some particular categories evolved in the second term of the year (in fact, since we have information on the two-week when the household provided information, we can identify that the lockdown started in March the 14th -week 12 of 2020-). To get a sense of which type of expenditures were -on aggregate of the subgroup- most affected during the term in which the lockdown occurred, a visual representation of some categories whose level in 2020 is statistically different (at 5 percent level) to the 2019 one is provided. We group in Table 1 different groups most affected by the lockdown.

Group	**Goods**
Housing	Home Services, Durables, Furniture, Electricity, Clothing
Restricted Availability	Hotels & Restaurants, Transportation, Leisure, Health
Food and Drinks	Lamb, Butcherie, Fish, Coffe, Sodas, Alcoholic Drinks

Table 1: Goods aggregation

During the second term of 2020 the aggregate expenditure in food and drinks significantly increased with respect to to the same quarter of 2019 (Figure 1). Figure 2 shows how expenditure on some durable goods or purchases of clothing and furniture also had a pronounced decrease during the lockdown.

[3] See Prais (1958) for alternatives to measure the cost of living.

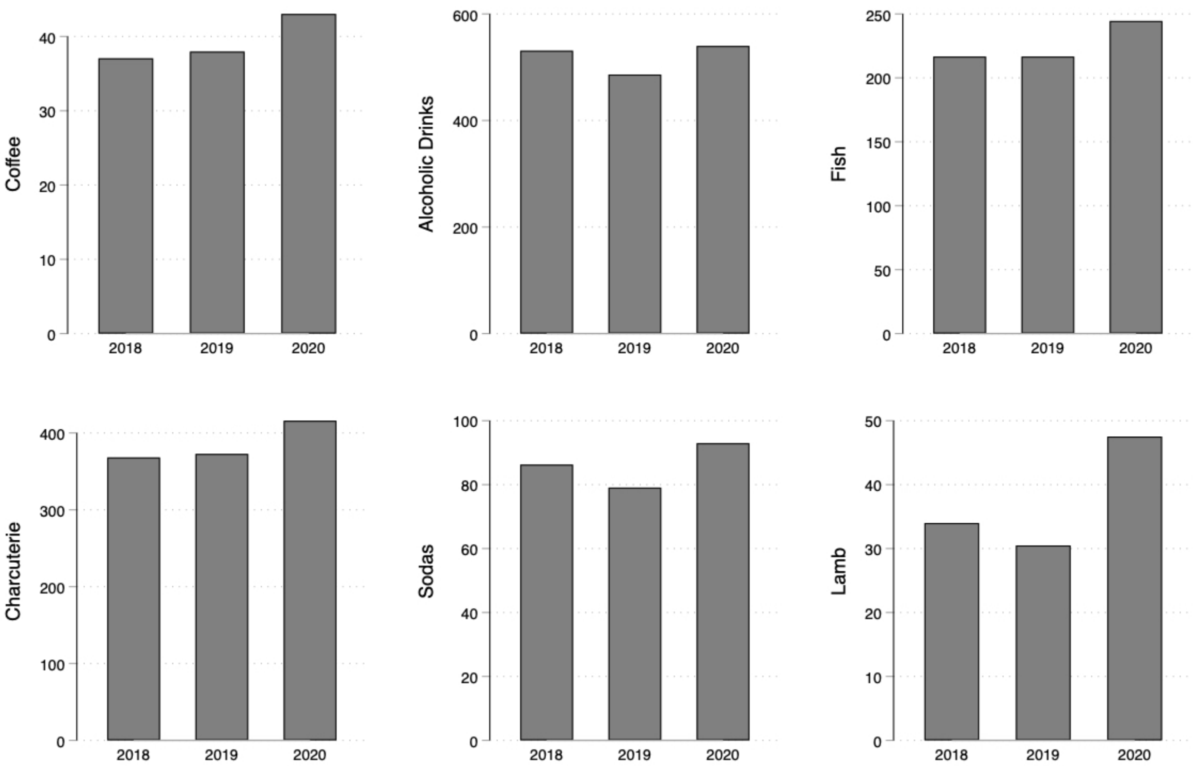

Figure 1: Expenditure in food and drinks

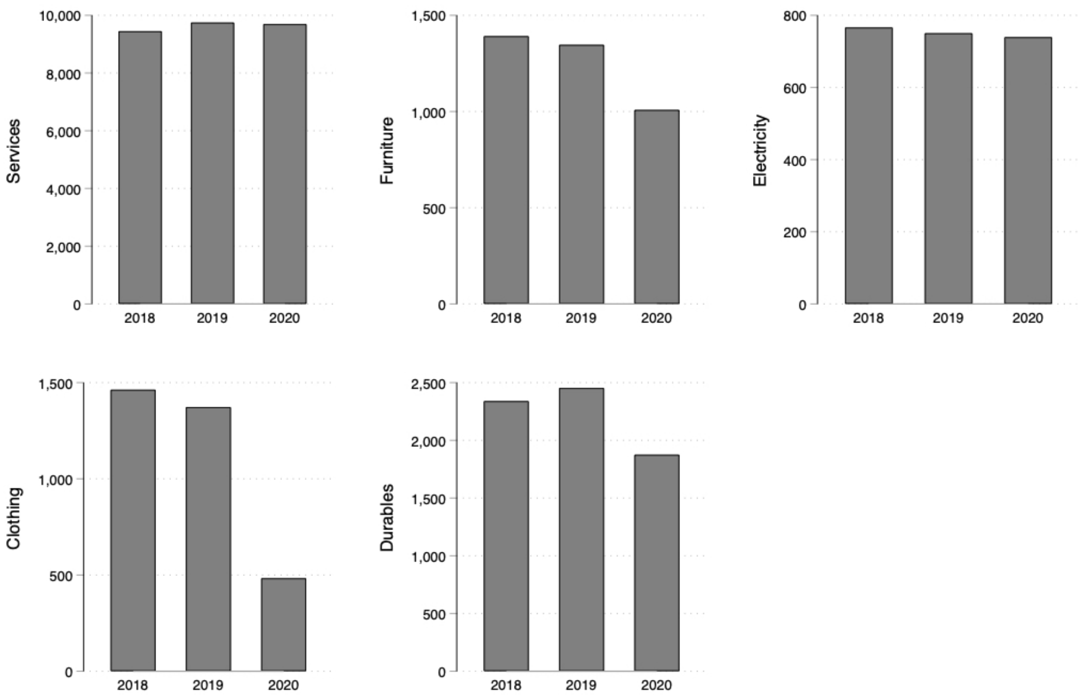

Figure 2: Expenditure in housing items

Figure 3 depicts a sharp decrease in expenditure of all the *activities* that households were not able to carry on due to lockdown restrictions affecting mobility. The most obvious categories reflecting it are expenditure in restaurants and hotels, leisure expenditure or transportation expenditure. For instance, during the second quarter of 2020, the decrease in expenditure in restaurants and hotels experienced by Spanish households was prominent, being 80 percent less than in 2019.

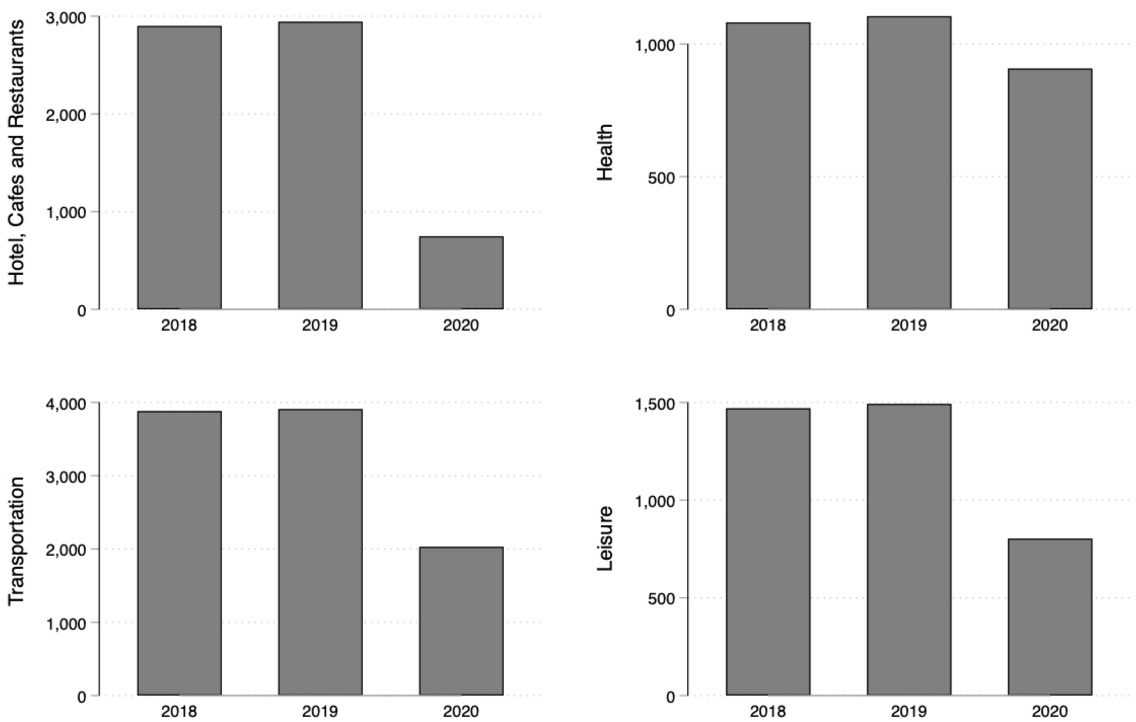

Figure 3: Expenditure in items with restricted availability

3 Empirical Strategy and Model

3.1 Definition of the Treatment samples

In order to have a more complete assessment of how the lockdown affected expenditure, we estimate both unconditional and conditional DiD and RDD models. This approach, while naive, allows us to better capture the effect of the lockdown on each type of expenditure (up to 114 different items).

For both exercises the baseline sample is defined on the basis of the 2020 survey observations. Those household interviewed after 14/03/2024 are potential treated observations. Alternatively those household interviewed before the lockdown (but in 2020) are potential controls.

For the DID, we use all those household with consecutive observations in 2019 (before) and 2020 (after) that are interviewed in the same portion of the year (as defined by the lockdown date) in both years.

In words, the sample comprises individuals who had two interviews, the first one being in 2019. The treatment group contains households that had the second interview after the lockdown (and the first interview in the same period of 2019), and the control group those households that had the second interview before the lockdown (and the first interview in the same period of 2019).[4]

For the RDD, we have a sharp design in which the treatment variable is constructed in the following way:

$$T_{rdd} = \begin{cases} 1 \quad \textit{if} \;\; i_1 \;\; \text{or} \;\; i_2 \in [Lockdown, 31/12/20] \\ 0 \quad \textit{if} \;\; i_1 \;\; \text{or} \;\; i_2 \in [01/01/20, Lockdown) \end{cases}$$

As stated before, an individual is part of the sample if he had an interview during 2020. If the interview was carried on before the lockdown, the household belongs to the control group, and if it was done after the lockdown, the household belongs to the treatment group. As the second interview takes place about one year after the first one (in the same week of the year), we observe no cases in which an individual is classified in both groups.

In both exercises we explore alternative definitions of the sample by restricting the time span around the lockdown starting date. We use three time windows: the whole 2020, 5 weeks before and after the lockdown (two and a half months before and after) and 2 weeks before and after the lockdown (one month before and after). In both cases we define the placebo sample by moving one year back the corresponding DiD and RDD samples. That is in the case of DiD we compare Treated and Control observation in 2018 and 2019. Alternatively in the case of the RDD we compare early and late in the year 2019 sample. The cutoff is defined on the basis of the lockdown starting date (14/03/2020).

3.2 Unconditional analysis

Given the design of the sample, we expect both treated and control groups to be identical. Even if this is the case, we provide a summary of statistics for both groups and we test for differences in averages for the relevant covariates (for the DID design,

[4]At this stage, we only look at the effect during the strict first lockdown, but the evolution of the pandemic made both central and regional governments to adopt different less strict measures, which could be set-up in a staggered framework as in Callaway and Sant'Anna (2021).

for the RDD see the first table on the appendix). All this information is contained in Table 2. The only unexpected difference is in the number of dependent children (and correspondingly teen members).[5] Head of households in the treated group are between 3 months and 1 year older than heads of household in the control group due to the way the information is collected.

Table 2: Mean over treatment, whole sample

Variable	(1) Control	(2) Treated	(3) P-Value
Age	56.04	56.87	0.004
Education Level 1-2	16.67%	16.88%	0.5 (Joint Education)
Education Level 3-4	47.78%	47.49%	–
Education Level 5-6	19.43%	19.96%	–
Education Level 7-8	16.12%	15.66%	–
Dependent Child	0.636	0.589	0.04
Number of Active Members	1.03	1.03	0.896
Teen Members	0.473	0.427	0.004
Adult Members	1.684	1.671	0.585
Elderly Members	0.497	0.508	0.481
Log Income	5.41	5.38	0.630
Occupation	5.02	5.21	0.662
N	3114	11978	

[5]The information provided by the survey does not allow us to know the reason for these discrepancies, but our guess is that the lockdown caught them away from home, for study reasons, and they were unable to return.

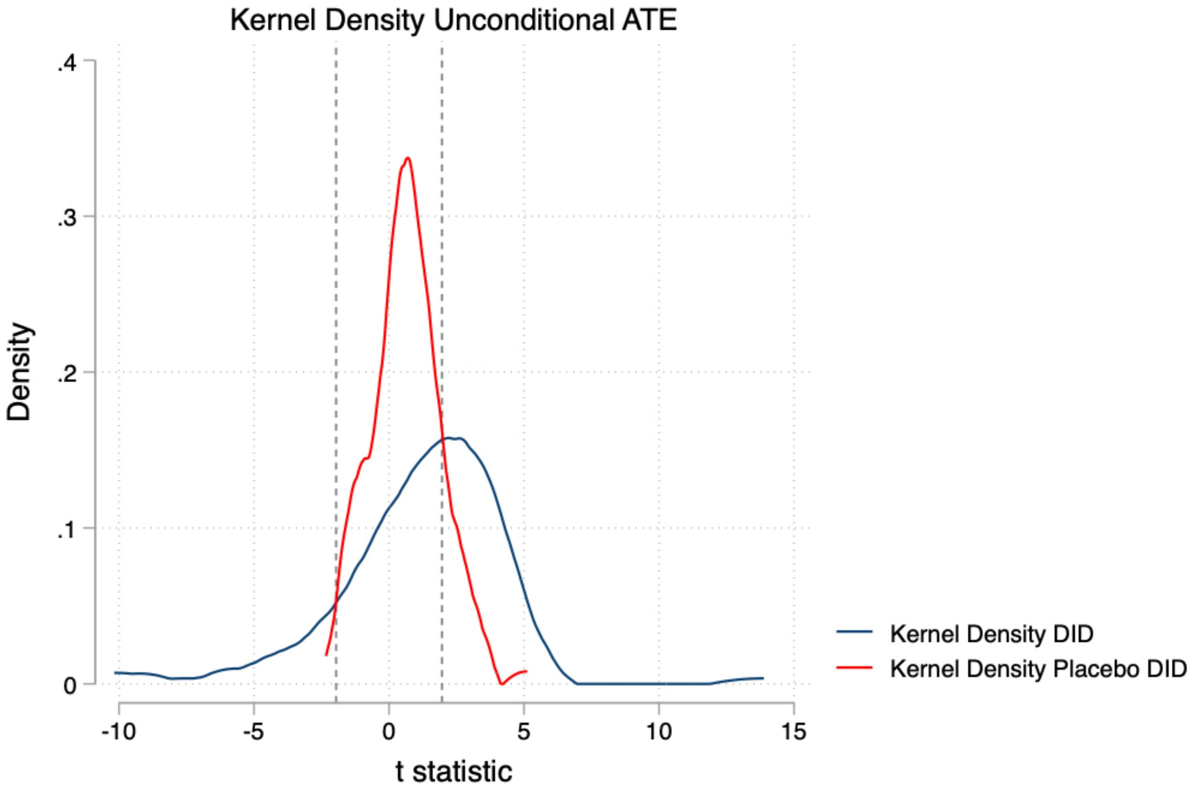

Figure 4: DID Kernel

DID vs placebo DID: we first explore the unconditional treatment effect (average change) of the lockdown on every expenditure item and we adjust a Kernel density on the t-statistics for 114 consumption categories (see Figure 4). In the same figure, the Kernel density for a placebo treatment defined the same way but a year before is also plotted. As one would have expected, the tails (both left and right) of the density constructed with lockdown estimates are much more pronounced, which reinforces the belief that the lockdown significantly changed expenditure for many consumption items or groups. On the other hand, the vast majority of the placebo estimates lies within the insignificance region.

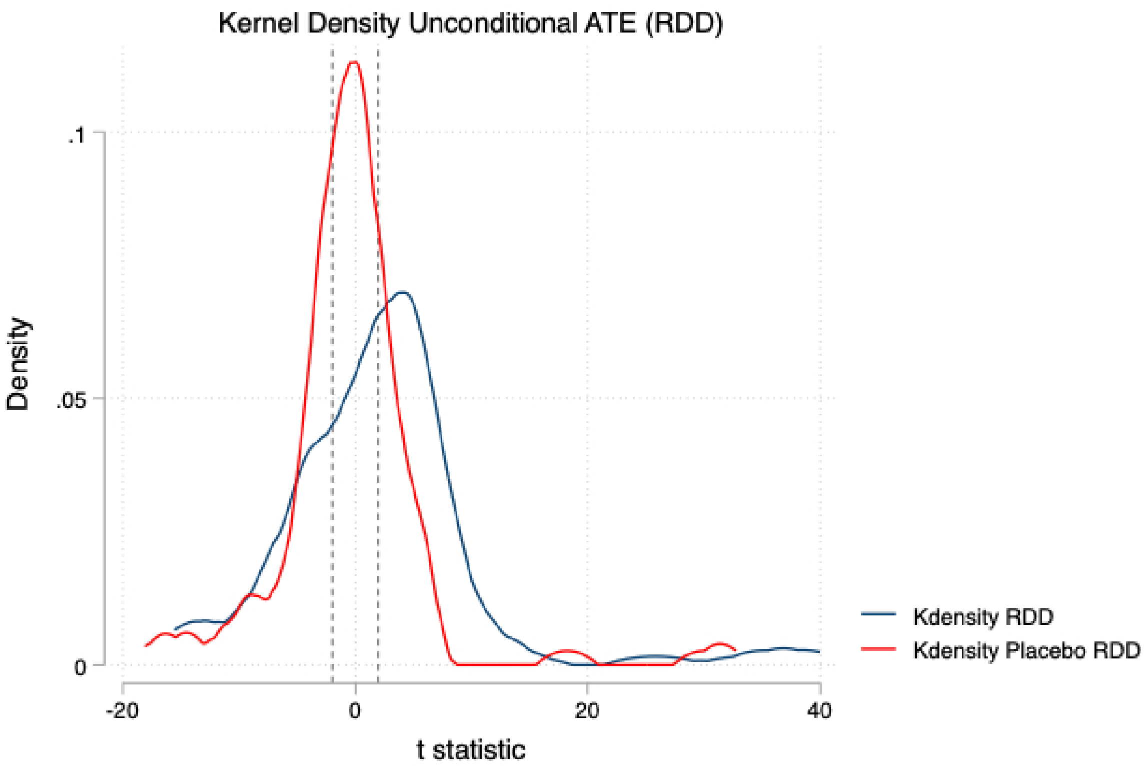

Figure 5: RDD Kernel

RDD vs placebo RDD. The same comparison between the treatment effects of the lockdown and the placebo is preformed the RDD estimates (see Figure 5). In this case, the difference is not as striking as in the DID, especially for the right tail since once strict lockdown finished most goods became again available to the consumers. However, the density is much more concentrated around 0 for the placebo treatment.

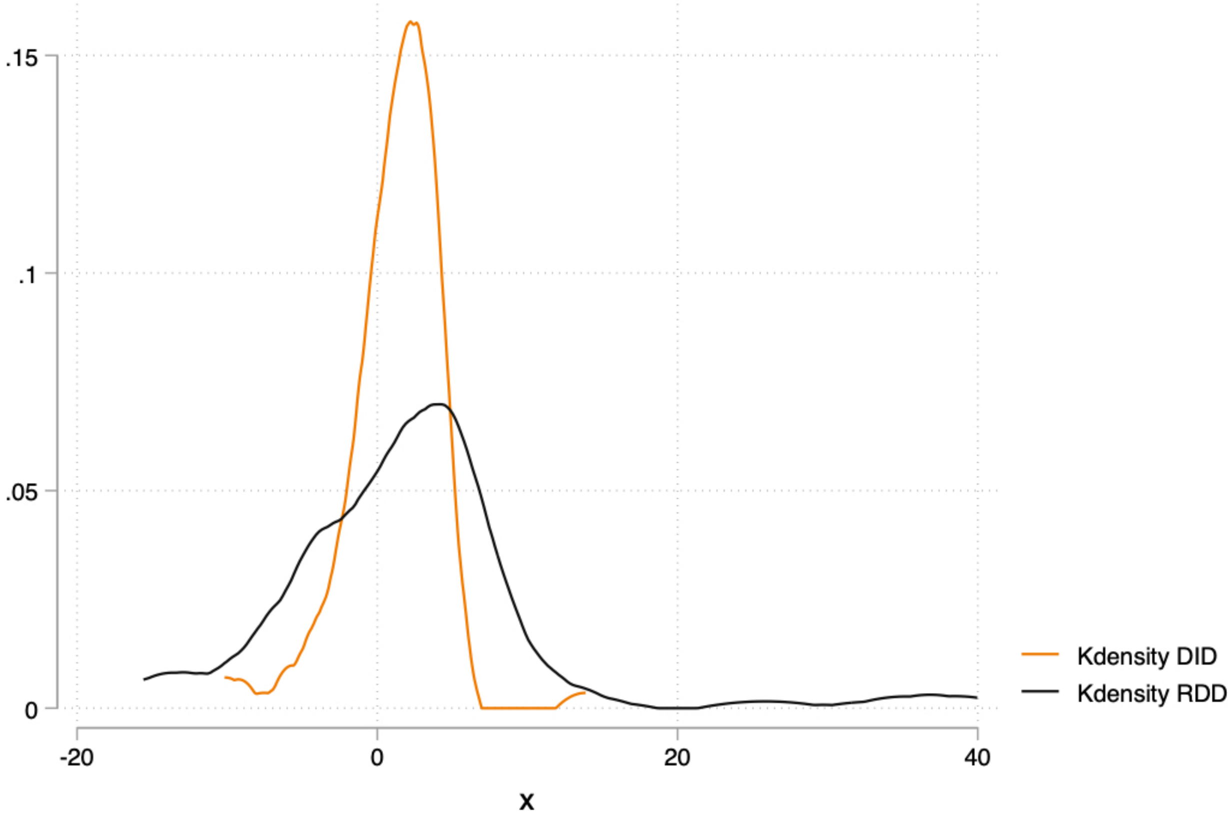

Figure 6: Kernel DID vs RDD

DID vs RDD. Finally, we compare t-statistics for the lockdown effects of both RDD and DID estimates (114 consumption categories). Figure 6 clearly shows that the tails of t-statistics corresponding to the RDD results are significantly much wider that the ones for the DID one. This is not surprising, given the fact that the sample size is notably larger for the DiD procedure due to the way the treatment is designed. As a consequence, the t-statistics for the RDD tend to be larger (in absolute value). Examples of this are the sharp decrease in clothing expenditure (not available during the strict lockdown, and with limited availability afterwards) for which the t-statistic of the RDD more than doubles the DID one (-6.05 vs -2.39). Other examples of this are transportation expenditure and expenditure on items that could be considered luxury food (lamb, seafood,...).

3.3 Conditional analysis

We assume that the baseline specification for estimating the average treatment effect (ATE) of the lockdown on expenditure in category j takes the form of a structural demand model:

$$ln(EXP_{itj}) = \alpha + \beta ln(P_{itj}) + \gamma ln(Y_{it}) + \delta X_{it} + \theta T_{it} + \varphi_i + \phi_t + \varepsilon_{itj} \qquad (1)$$

Where $ln(EXP_{itj})$ denotes the natural log of expenditure in a particular category j in real terms, $ln(P_{itj})$ measures the CPI-adjusted natural log of the real price of good j and $ln(Y_{it})$ measures total expenditure. Since equation (1) corresponds to a intratemporal demand model, we follow Deaton and Muellbauer (1980) two stage budgeting assumption and use total expenditure instead of income. X_{it} is a set of socioeconomic controls, among which we include household size and structure, educational level of the head of the household, number of dependent children, municipality size, age and occupation sector of the head and regional dummies. We also include a quarterly dummy to control for potential seasonality of expenditure. φ_i and ϕ_t are the household and year fixed effects. T is our treatment dummy. We present OLS estimates of (1) using DID and RDD treatments as defined in section 3.1.

3.4 Effects on demand

The results of the OLS estimates of equation (1) are provided in Table 3. We use the whole sample of wave 2020 to estimate each specification, leading to a larger sample size. Given the way treatments are defined in the DID and RDD settings, we obtain a larger sample size in the latter case. However, in the next section we present results with restricted samples.

The treatment effect here provides information about mid-term changes in consumption behavior rather than capturing the immediate response of households generated by the lockdown. In latter sections of the paper we use smaller time windows to provide shorter-term effects.[6]

[6] We only define a treatment for the lockdown happening in March 2020. We are aware that the Spanish government decreed another lockdown in November and the Spanish regions adopted restrictive measures at several times during the year. We are not considering it in this paper.

Table 3: ATE estimates whole sample (2020 wave of the EPF)

	Total	Food	Transport	Lamb	Services
DID_{ws}	-.096***	.085***	-.477***	.747***	-.296***
	(.020)	(.025)	(.064)	(.134)	(.027)
N	14514	14401	12573	7051	14508
RDD_{ws}	-.059***	.059***	-.426***	.653***	-.227***
	(.009)	(.011)	(.029)	(.054)	(.012)
N	18441	18363	15582	9142	18558

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results indicate that aggregate expenditure went down significantly as a result of the lockdown. Both the DID and the RDD estimates suggest that the lockdown decreased total expenditure by a corresponding annual figure of 6-10 percent. In general, expenditure decreases for most of the expenditure items, except for food. The increase in food expenditure varies from 8.5 percent (DID) to 5.9 percent (RDD). This increase is particularly remarkable in subcategories which we could define as ”fancy food” that could be considered as a substitute for meals outside home. An example of this is lamb, whose expenditure more than doubled according to our DID coefficient. Transportation and services expenditure also experienced sharp decreases either using DID or RDD treatments. Although the estimated coefficients vary within estimation methods, the 95 percent confidence interval of the DID point estimate contains the RDD coefficient in all cases but in services.

Figure 7 plots the kernel densities for the t-statistics of lockdown effects for all 114 expenditure categories. The RDD displays fatter and longer tails, but as in the case of the DID, the majority of the density is concentrated in the 5% significance region of the figure (outside the grey dashed lines). We can conclude from these results that most of the expenditures were significantly affected by the lockdown either with increases or decreases.

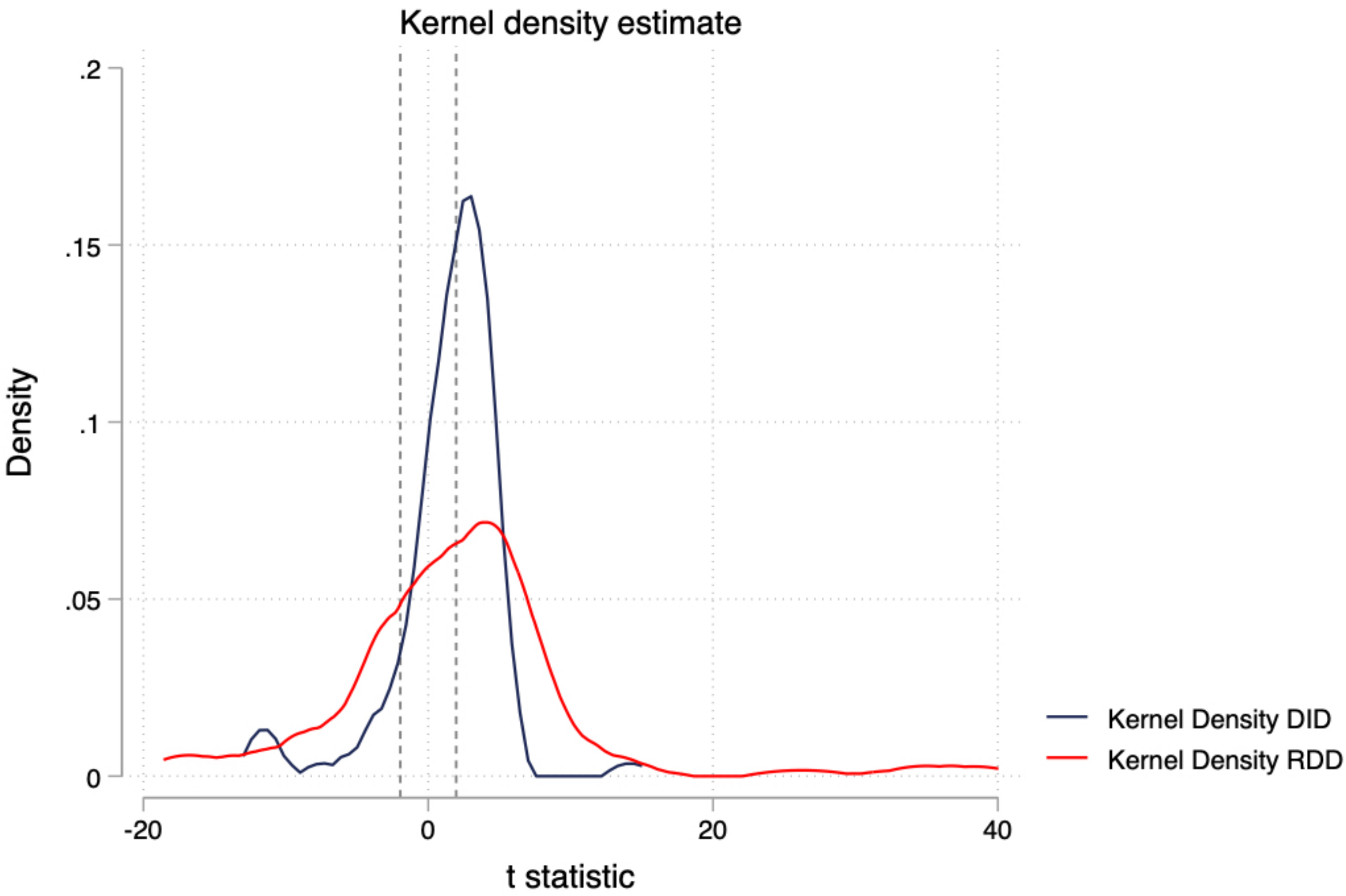

Figure 7: RDD and DID t-statistics

3.5 Differentiating effects on participation and demand

To further assess how the lockdown affected certain consumption habits, we study those items experiencing a significant change in the percentage of households consuming them. One could think that the pandemic had not only influenced the amount of expenditure of certain goods and services, but also the decision of purchasing them. Among all groups of expenditure, we selected those experiencing a larger drop (increase) in the number of households spending a positive amount of money in that group. We adjust a model including both a participation and demand equations to get a picture of the lockdown effect in both decisions. We use a standard two-stage sample selection model *à la* Heckman (1979).

$$D_{itj} = \Phi(\alpha + \beta ln(P_{itj}) + \gamma ln(Y_{it}) + \delta X_{it} + \varphi Z_{it} + \theta T_{it} + \phi_t + \zeta_{it}) \tag{2}$$

Equation (2) represents the first stage -participation equation- of the sample selection model. The dependent variable D is a dummy variable which equals 1 if household i purchased any monetary amount of item j at time t and 0 otherwise. Besides, Z contains the determinants of participation not included in the demand equation (identification restrictions), being the rest of variables the same as in (1). The resulting demand equation differs from (1) in the addition of a correction term (inverse of Mill's ratio) obtained using parameter estimates in (2).

Estimates of the treatment effect in both the first stage (participation) and the second stage (demand) are reported in Table 4, again using the whole sample of the 2020 wave of the survey. Note that we present marginal effects for participation estimates. To keep size of the tables at a minimum We do not report correction terms in the table.[7]

From the results in Table 4 we see that there is a sharp decrease in the probability of spending positive amounts in clothing. However, for those that expend clothing expenditure was unaffected by the lockdown. The case of leisure presents a clear result: both the probability of consuming and the amount consumed decreased. For the restaurants, coffee stores and hotels category (RCH) the lockdown decreased by more than 22 percentage points the probability of spending while overall expenditure decreased around 50%. As the whole sample is being used (all of 2020), we expect for the RCH category much more negative estimates for the marginal effects in both stages as we shorten the period, given that restaurants reopened some months after the first lockdown in March. Later sections will explore this issue.

In the previous section, we argued that "fancy food" expenditure experienced a remarkable increase, probably due to households substituting meals outside. Here our results suggest that the overall increase comes from a much higher level of expenditure among those consuming rather than an increase in the probability of consuming, given that the probability of spending remained unchanged while expenditure increased around 80%.

[7]Some of the selection terms are non-significant. We attribute non-significance to the fact that non-consumption of items could correspond to infrequency of purchase of the good (remember that households provide information in a two-week period) or corner solutions (some goods are not purchased at any given value of prices or household income). For the sample selection model to be an adequate specification, zeros should correspond to potential consumers non-participating at the time they provide information on demand.

Table 4: Two Step Treatment estimates (2020 wave of the EPF)

Stage	Clothing	Leisure	R,C,H	S-Durables	Seafood
Participation$_{ws}$	-.145***	-.080***	-.226***	-.094***	-.014
	(.017)	(.015)	(.016)	(.015)	(.019)
Demand$_{ws}$	-.055	-.161***	-.709***	-.453***	.583***
	(.052)	(.059)	(.070)	(.073)	(.146)
N	14597	14597	14597	14597	14597

R,C,H stands for Restaurants, Cafes and Hotels

S-Durables stands for Semi-Durables

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.1 Tobacco and Alcohol Expenditure

In the last section, we pointed out that the estimates for clothing and seafood suggested large lockdown effects on the subsample of households with positive expenditure. While these results are interesting, we will devote this section to analyze the effect on the subsample of positive expenditure for other categories that have much more relevant policy implications in terms of, for example, health.
Following this lines, we analyze whether alcoholic drinks and tobacco were affected during the lockdown. We guess that, while the habit of consuming these substances may not be affected for those households that were already spending positive amounts of these items, the lockdown may have had a positive impact on its expenditure. Thus, we model tobacco and alcohol expenditure with the two-step procedure and the compute the effect of on the expected conditional log consumption:

$$Pr\Big(D_{it,tob/alc} = 1\Big) = \Phi(\delta Z_{it} + \theta T_{i,t})$$

$$E[log(Exp_{it,tob/alc}) \mid D = 1, X_{it}, T] = \beta X_{it} + \gamma T_{it} + \sigma_{\varepsilon,\nu}\lambda(\delta Z_{it} + \theta T_{i,t})$$

The marginal effect of the lockdown on households with positive expenditure is given by:

$$\frac{\partial E[log(Exp_{it,tob/alc}) \mid D=1, X_{it}, T]}{\partial T} = \gamma + \sigma_{\varepsilon,\nu} \frac{\partial \lambda(\delta Z_{it} + \theta T_{i,t})}{\partial T} \tag{3}$$

The results for alcoholic drinks are reported in Table 5. The upper part of Table 5 displays the lockdown effect on the first and second stages together with the estimated parameter for the correction term and the marginal effect of the treatment on the Inverse Mills ratio. In the lower panel we report the average marginal effect on conditional log consumption. As the statistical software is unable to provide the distribution of the treatment effect for the subsample of positive expenditure when using the two-step procedure, we use a bootstrap procedure. We report both the bootstrap estimate and the same estimate but when employing the subsample that was not part of the bootstrapping process. In Table 5 we observe that while the lockdown did not affect the probability of spending, overall expenditure increased by roughly 37%. As seen by the bootstrap estimates, this effect is carried out entirely by the proportion of individuals who spent a positive amount.

Table 5: Alcohol Two Step estimates (2020 wave of the EPF)

Stage	Treatment	$\widehat{\sigma}_{\nu,\varepsilon}$	$\widehat{\lambda}'_T$	$\widehat{ME}$
Participation$_{ws}$	-0.019			
	(.018)			
Demand$_{ws}$	.367***	-.523	.029	
	(.085)	(0.401)	(.029)	
Bootstrap (Used)				0.370***
				(.019)
Bootstrap (Not used)				0.348***
				(0.002)
N	14514	14514	14514	14514

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Tobacco Two Step estimates (2020 wave of the EPF)

Stage	Treatment	$\widehat{\sigma}_{\nu,\varepsilon}$	$\widehat{\lambda}'_T$	$\widehat{ME}$
Participation$_{ws}$	-0.072***			
	(.017)			
Demand$_{ws}$	.088	.176	.178***	
	(.131)	(.415)	(.042)	
Bootstrap (Used)				.103***
				(.027)
Bootstrap (Not used)				0.119***
				(0.004)
N	14514	14514	14514	14514

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We repeat the former analysis with tobacco expenditure and report the results in Table 6. In this case, we observe that overall expenditure remained unaffected by the lockdown. However, the probability of spending decreased by 7.2 percentage points. Given that the proportion of people consuming tobacco decreased but total expenditure remained unchanged, we may infer that those that still consumed increased their expenditure. This is confirmed by the bootstrap estimates: tobacco expenditure increased between 10-12% for those that consumed. This suggests that a fraction of individuals tried to quit smoking and the fraction that did not exacerbate its consumption.

4 Sample Heterogeneity

In this section we explore the heterogeneity of the results to variations of the sample. We first explore the consequences of using shorter time spans to define treated and control household. Then we explore the heterogeneity of the results by age and income groups.

4.1 Shorter time spans

In the previous sections, we mentioned that using the whole sample might have lead us to estimate mid-term effects rather than short term effects of the lockdown. In this subsection we replicate previous analyses with two alternative time spans. The first uses the 2 months and a half before and after the pandemic stroke (*strict lockdown*). The second contains only households interviewed within one month before and after the lockdown.[8]

4.1.1 DID and RDD effects on demand with alternative time spans

Table 7 displays the results for all of the 3 time spans utilized, which comprises the sample for one month before-after the treatment (first panel), the sample of two and a half months (second panel) and the whole sample (third panel, *i.e.*, the same results presented in Table 3). Thus, the pre-treatment group for the two and a half months is identical to that of the previous section, while the post-treatment group has been reduced. For the sample containing one month before and after the lockdown, both the sizes of the pre-treatment and post-treatment groups are reduced.

From the results of Table 7, we observe that estimates for transportation expenditure are now notably smaller and indicate that this service was affected to a point that it was not available during that period. This decrease is even more lousy for the shortest period. Evidence suggests that food expenditure increased slightly more in the short term (one month and two and a half months time spans) than in the medium term. We obtain much larger estimates for lamb meat consumption, as expected, suggesting that the substitution between restaurants and fancy cooking at home was prominent in the first months after the lockdown when people were completely unable to eat outside. A similar effect is observed for the aggregate of expenditure in services.

[8]In the Appendix we provide descriptive statistics for the treatment and control groups using these alternative definitions.

Table 7: ATT estimates by different time spans (2020 wave of the EPF)

	Total	Food	Transport	Lamb	Services
One month					
DID_{1mo}	-.321***	.161***	-1.147***	1.413***	-.360***
	(.042)	(.052)	(.140)	(.276)	(.056)
N	2464	2452	2078	1227	2481
RDD_{1mo}	-.278***	0.098***	-0.971***	1.121***	-.366***
	(.018)	(.022)	(.071)	(.111)	(.027)
N	3331	3305	2711	1606	3363
Two and a half m					
DID_{2mo}	-.174***	.134***	-.970***	1.275***	-.450***
	(.025)	(.031)	(.084)	(.165)	(.034)
N	6193	6168	5304	2963	6218
RDD_{2mo}	-.172***	.119***	-.927***	1.121***	-.420***
	(.011)	(.014)	(.041)	(.067)	(.016)
N	8476	8432	7097	4045	8531
2020 wave					
DID_{ws}	-.096***	.085***	-.477***	.747***	-.296***
	(.020)	(.025)	(.064)	(.134)	(.027)
N	14514	14401	12573	7051	14508
RDD_{ws}	-.059***	.059***	-.426***	.653***	-.227***
	(.009)	(.011)	(.029)	(.054)	(.012)
N	18441	18363	15582	9142	18558

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Given the difference in treatment assignment between DID and RDD, the sample of treated and controls is smaller in the first case as the requirements for being either treated or control are indeed more restrictive for the DID. This comes at a caveat: we find that DID estimates are somehow less precise than the RDD ones. This last result could also be caused by differences between the individuals that belong to RDD and the DID sample. To check that the difference in precision is only caused by different sample sizes, we tested whether the sample groups for RDD and DID were the same for each time span. Results confirm that indeed the groups look pretty much alike, as it could be expected by both the random nature of the sampling and interview selection processes.

4.1.2 Two-step models with alternative time spans

We now repeat the analysis of estimating sample selection models using the three different time spans. The results are displayed in Table 8. Again, the results are organized in the three panels.

The observed tendency is usually negative estimates for the first stage accompanied by even larger negative effects for the demand stage. The most clear example is the RCH expenditure. While the probability of spending a positive amount of money in restaurants, coffee shops or hotels decreased 45 percentage points, the expenditure dropped to 0 for the shortest time span. This does not come as a surprise as all these establishments were closed and there was no possibility of spending. As mentioned before, we can infer that the unavailability of meals outside was substituted by ”fancy food”, which seems the case as suggested by the fact that seafood expenditure increased around 275%.

The fact that the first-stage estimates are smaller (in absolute value) does not come as a surprise. As opposed to the second stage, they are bounded by the proportion of households spending positive amounts in a particular category, which in most cases is not even close to 1. The close to 40 percentage points decrease in the proportion of consumers for the cases of clothing and RCH category implies that (almost) everybody stopped consuming those goods.

Table 8: Two Step Treatment estimates by different time spans (2020 wave of the EPF)

Stage	Clothing	Leisure	R,C,H	S-Durables	Seafood
One month					
Participation$_{1mo}$	-.399***	-.137***	-.417***	-.233***	-.074*
	(.030)	(.032)	(0.029)	(0.032)	(.040)
Demand$_{1mo}$	-.307	-.209	-1.956***	-0.750***	1.327 ***
	(.456)	(.137)	(.257)	(.160)	(.342)
N	2481	2481	2481	2481	2481
Two and a half m					
Participation$_{2mo}$	-.322***	-.120***	-.361***	-0.186***	-.055**
	(.019)	(.019)	(.018)	(.018)	(.024)
Demand$_{2mo}$	-.501***	-.444***	-1.741***	-.760***	.838***
	(.201)	(.083)	(.147)	(.100)	(.201)
N	6222	6222	6222	6222	6222
2020 wave					
Participation$_{ws}$	-.145***	-.080***	-.226***	-.094***	-.014
	(.017)	(.015)	(.016)	(.015)	(.019)
Demand$_{ws}$	-.055	-.161***	-.709***	-.453***	.583 ***
	(.052)	(.059)	(.070)	(.073)	(.146)
N	14597	14597	14597	14597	14597

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Income and age heterogeneity

In what follows we explore whether we have treatment heterogeneity in terms of income and age. We estimate the ATT using only the whole sample (2020 wave) for groups composed by individuals aged above and below the median age (56). These results are presented in Table 7, where we also present for comparison those corresponding to ATT without any distinction.

Table 9: ATT estimates by age group (2020 wave of the EPF)

	Total	Food	Transport	Lamb	Services
DID_{ws}	-.096***	.085***	-.477***	.747***	-.296***
	(.020)	(.025)	(.064)	(.134)	(.027)
N	14514	14401	12573	7051	14508
$\text{DID}_{ws}, 56^{-}$	-.117***	.135***	-.410***	665***	-.326***
	(.028)	(.033)	(.081)	(.185)	(.035)
N	7405	7397	6973	3554	7457
$\text{DID}_{ws}, 56^{+}$	-.079***	.030	-.563***	.839***	-.262***
	(.028)	(.038)	(.103)	(.194)	(.040)
N	7109	7077	5651	3523	7731

56^{+} is the group above the median age.

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimates for total expenditure are significantly different from zero at standard levels for all the samples. However, the coefficients for the whole sample and the two age subsamples are very close and we cannot reject the equality of the coefficient at 5 percent significance. The most striking differences are for transportation and services expenditures, but the 95% CI for the whole sample estimate contains both of the heterogeneous estimates. The differences, if any, could be due to more cautious behavior of the older individuals during and in the aftermath of the lockdown as they faced severe health risks. The only remarkable difference is that we observe no effect on food expenditure for those households whose head is older than the median.

We also form treated and control groups with households' income for the bottom and top 20 percent of the income distribution, *i.e.*, at the second and eighth deciles. These estimates are reported in Table 10. We observe that the high-income households are the ones that decreased expenditure significantly, while this is not true for the low-income ones (in 3/5 categories). This could be due to the impossibility of dining out, buying furniture or shopping for clothing items, categories whose consumption is luxury and less frequent for low-income individuals, who devote most of their expenditure to the purchase of necessities. We do not find significant differences between the results for the whole sample and the results for the top 20 percent of the richest households with the exception of lamb expenditure. There are no differences between the two income groups with again the exception of lamb expenditure. Rich households increased significantly the consumption of meat while the lockdown did not affect the amount devoted to this food item by poor households. The average estimates obtained for food at home are in line with those of Baker *et al.* (2021).

Table 10: ATT estimates by income group (2020 wave of the EPF)

	Total	Food	Transport	Lamb	Services
DID_{ws}	-.096***	.085***	-.477***	.747***	-.296***
	(.020)	(.025)	(.064)	(.134)	(.027)
N	14514	14401	12573	7051	14508
$\text{DID}_{ws,p20}$	-.099	.058	-.402**	.323	-.198**
	(.063)	(.088)	(.203)	(.349)	(.093)
N	2094	2115	1381	920	2169
$\text{DID}_{ws,p80}$	-.104***	.103**	-.479***	1.085***	-.269***
	(.039)	(.048)	(.120)	(.298)	(.043)
N	3306	3299	3174	1746	3306

$p80$ and $p20$ indicates the 80 and 20 income percentiles

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Robustness checks

5.1 Treatment placebo

In this section we perform a series of robustness checks. The first one consists in obtaining DID estimates for a placebo treatment defined in the section 3.1 of the paper. In particular, we re-estimate the model on the 114 goods and present a Kernel density to compare the two set of results.

The Kernel density for the placebo treatment estimates is highly concentrated in the acceptance region (Figure 8), *i.e.*, where we cannot reject the null that the coefficient is zero (78,3% of the coefficients do not vary at the time of the lockdown), while the actual treatment spans along a wide area of the rejection region, with both significantly negative and positive estimates (only 36% of the coefficients do not show a significant variation due to the lockdown). This suggests that indeed the lockdown had a significant effect on the demand of Spanish households.

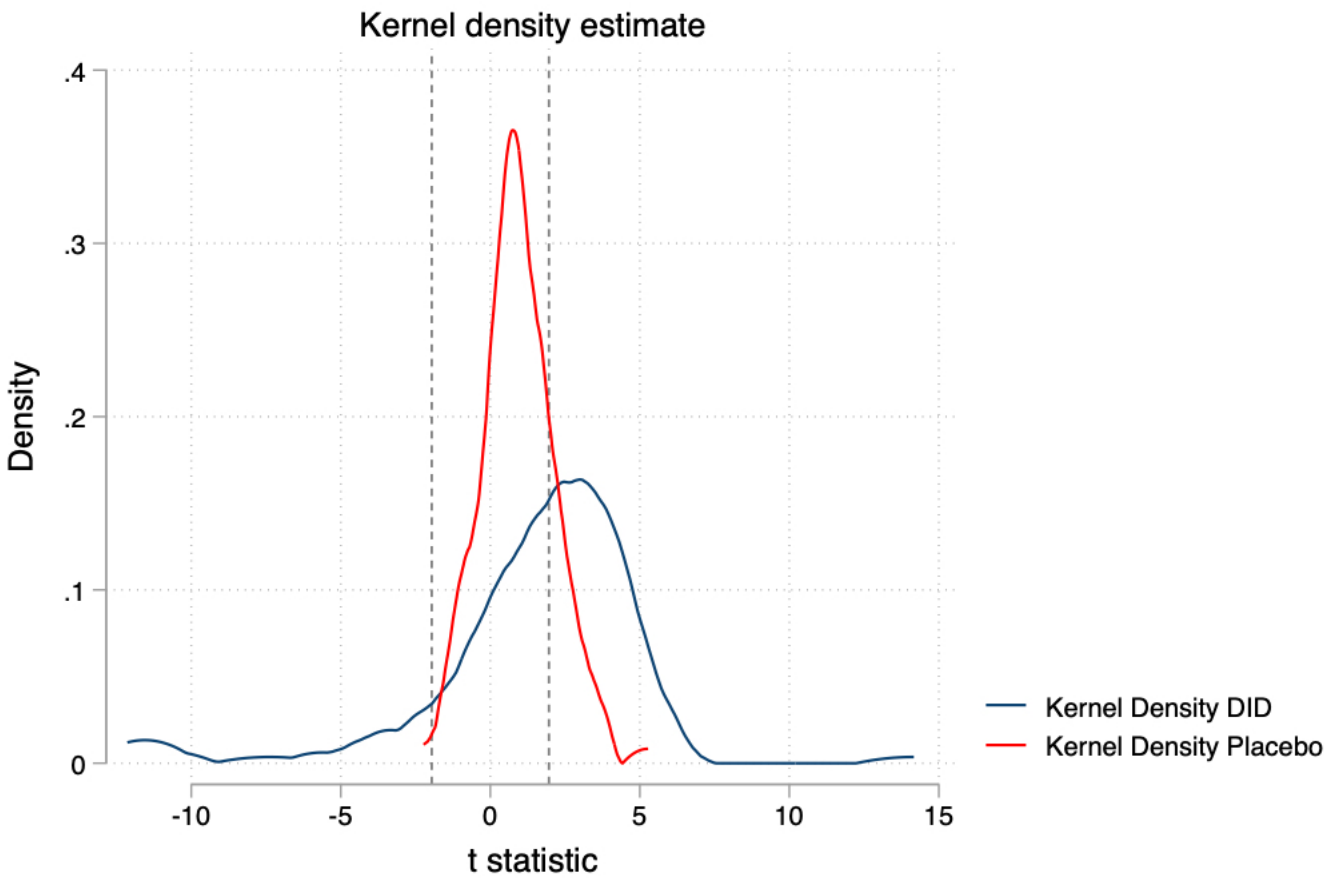

Figure 8: Whole Sample DID vs Placebo

Table 11 compares the true DID estimates and the placebo ones on the same categories of consumption used in Tables 3 and 5. We cannot reject the null that the parameter is zero for practically a vast majority of the estimates in the placebo experiment (already tested in Figure 10). Notable exceptions in this Table are the Total and Lamb expenditures. We reinforce the previous findings by estimating two-step sample selection models whose results are displayed in Table 12 for both the true lockdown and the placebo samples. In this case, treatment parameters of both participation and demand equations are not significant for the placebo experiment.

Table 11: ATT estimates (2020 wave of the EPF) vs placebo (2019 wave of the EPF)

	Total	Food	Transport	Lamb	Services
DID_{ws}	-.096***	.085***	-.477***	.747***	-.296***
	(.020)	(.025)	(.064)	(.134)	(.027)
N	14514	14401	12573	7051	14508
DID_{pla}	-.056***	-.013	-.036	.406***	-.025
	(.019)	(.023)	(.062)	(.126)	(.027)
N	15071	14979	13293	7296	15068

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Two step estimates (2020 wave of the EPF) vs placebo (2019 wave of the EPF)

Stage	Clothing	Leisure	R,C,H	S-Durables	Seafood
$\text{Participation}_{ws}$	-.156***	-.085***	-.237***	-.104***	-.019
	(.018)	(.015)	(.016)	(.015)	(.019)
Demand_{ws}	-.235***	-.381***	-.963***	-.223***	.490 ***
	(.084)	(.067)	(.081)	(.063)	(.166)
N	14514	14514	14514	14514	14514
$\text{Participation}_{pla}$	-.021	-0.007	-.002	-.017	-.016
	(.015)	(.013)	(.012)	(.012)	(.0186)
Demand_{pla}	-.047	.045	-.089*	-0.026	.151
	(.060)	(.054)	(.047)	(.050)	(.132)
N	15071	15071	15071	15071	15071

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Instrumenting Expenditure

The demand equations are fitted using total expenditure. Under the problem of errors in variables in expenditure components, total expenditure is contaminated by these errors and the estimates could be bias. Since our sample is a panel, we can estimate the demand model instrumenting expenditure at t with expenditure at $t-1$. Table 13 presents a comparison. With the caveat that the sample size when instrumenting with lag expenditure is half the sample size without instrumenting or instrumenting with income, the main results are confirmed and no major differences are observed.

Table 13: ATT estimates IV (2020 wave of the EPF)

	Food	Transport	Lamb	Services
DID	.085***	-.477***	.747***	-.296***
	(.025)	(.064)	(.134)	(.027)
N	14401	12573	7051	14508
IV: $log(exp_{t-1})$	.080***	-.482***	.651***	-.240***
	(.011)	(.049)	(.091)	(.020)
N	7217	6096	3351	7298
IV: $log(income)$	.138***	-.450***	0.748***	-.194***
	(.027)	(.064)	(.133)	(.033)
N	14401	12573	7051	14508

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Effects on savings and future consumption

In the previous section, we estimated that the average decrease in consumption spending of Spanish households ranged between 11-12%, potentially attributed primarily to constrained purchasing capacity across various goods and services. Nonetheless, this decline in consumption expenditure could also stem from heightened household vigilance amidst an economically unstable environment, leading to an increase in precautionary savings or apprehension regarding contagion risks. Regardless of the underlying cause for the downturn in consumption, an increase in household savings rate might be expected if adverse income shocks remain relatively modest. Crespo *et al.* (2023) illustrate how negative income shocks predominantly affected individuals enrolled in temporary labor force adjustment schemes lasting beyond six months; however, the implementation of public subsidies alleviated income reductions by up to 78% for this group. They also find that those who lost their jobs (or had to close their business), were most affected than those that kept their jobs with reduced income or were affected by a temporary layoff. We compute savings rates to evaluate the potential effects of the pandemic on future consumption by a breakdown of demographics.

6.1 Correcting income and consumption in the EPF

This subsection aims to scrutinize the nominal and real savings rate of households throughout the pandemic period and its proximate years. We seek to discern whether the stringent lockdown measures and other effects of the COVID-19 crisis influenced individuals' choices. However, the EPF survey data poses a notable challenge, as individuals tend to self-report their income and expenditures, sometimes inaccurately. To achieve an accurate estimate of savings, it is necessary to correct these self-reported figures. To address this, we use aggregate data from the National Accounts. Taking advantage of information on aggregate household savings, consumption, and income, we obtain correction factors for our survey data. After aggregating household income and expenditures, weighted according to the representativeness of individuals using grossing-up factors, we compare these values against those obtained from the National Accounts. We then use these comparisons to correct for self-reported household amounts. We then compare savings rates with and without corrections. If household income and expenditures are reported with the same error, i.e., if the reporting errors are household fixed effects, corrections are not necessary, except if we want to provide aggregate savings figures.

Once we have obtained the corrected income and expenditure figures, our next step involves computing savings. Initially, we calculate savings measures (aggregate savings and the savings rate) for the entire sample represented in 2017 to 2022. To avoid the impact of unexpected errors in income or total spending, we analyze in depth the distribution of household savings (and the savings rate) over our sample period. The survey data reveal that households in the bottom quintile of the distribution report expenditures in excess of income and the bottom 5% report borrowing needs that represent more than 100% of their incomes. On the other hand, only the top percentile reports an unexpectedly high savings rate. Thus, we discard the bottom 5% of and the top 1% of the savings rate distribution.

The behaviour of household savings appears more complicated than previously explained, as shown in Table 14. Column 1 presents the aggregate savings rates from 2017 to 2022, as reported in the National Accounts. Column 2 shows the calculated savings rate by year in the raw survey data, while column 5 shows the same raw data after excluding the bottom 5% of and top 1% of the savings rate distribution.

On the other hand, column 3 shows the savings rate once we apply the correction factors calculated as explained above to income and total expenditure. Both income and consumption from the survey account for about 65% of the aggregate National Accounts figures.[9] The pandemic even seems to affect the behaviour of Spanish households in terms of reporting income and expenditure information in the survey. Consequently, it is difficult to decide which series of savings rates to use to compute the heterogeneous behaviour of Spanish household savings, which we present below. To be consistent with the exercise, we use a single series corresponding to uncorrected savings rates, but from which outliers have been dropped (column 4).

Table 14: Comparison of savings rates

Type	National Accounts	EPF Uncorrected	EPF Corrected	EPF uncorrected selected	EPF corrected selected
2017	5,8	-12,91	-9,43	3,02	5,11
2018	5,55	-5,5	-4,52	4,34	4,88
2019	8,15	-2,61	0,21	6,54	8,3
2020	17,8	9,12	5,12	17,26	14,42
2021	13,78	7,65	4,47	14,71	12,41
2022	9,4	2,1	-1,98	10,13	7,32

The savings rate of Spanish households experienced an unexpected increase in 2020, attributed to the stringent lockdown measures enforced amidst the pandemic, along with consequential shifts in behaviour. These behavioral changes stemmed from heightened uncertainty, prompting precautionary saving, as well as a perceived risk of contagion, which unexpectedly bolstered savings. Notably, the savings rate in 2020 soared to 50% higher than the average savings rate observed during the period spanning 2007 to 2019. This rate remained unexpectedly high in 2021, a year in which some restrictions remained, and even in 2022, although we cannot attribute savings in 2022 to the effects of COVID-19, both because no longer pandemic-related restrictions were maintained and because other events occurred that may have affected the savings rate.

[9]These figures are 65% in 2017, 2018 and 2019, 63% in 2020 and 2022 and 64% in 2021 for total expenditure. For income, the figures are 63%, 64%, 62%, in 2017, 2018 and 2019, respectively, and 66% in 2020, 2021 and 2022.

7 Concluding remarks

We investigate the causal effect of the lockdown on household detailed consumption items as well as the household savings rate using data from the Spanish Household Budget Survey between 2017 and 20210.

Our analysis reveals that the lockdown induced important negative effects on the intratemporal distribution of total expenditure. Furthermore, the decline in total expenditure (around -10% in the case of DiD estimates and -6% in the case of the RDD estimates) masks different changes in commodity groups (for example the drop in Transportation is around -40% and the increase in Lamb consumption around 70%). We also found that the effect of the lockdown varied with the different stages of the pandemic, with the most severe changes being concentrated in the immediate weeks following the state of alarm.

Our findings also suggest that the lockdown measures, along with subsequent restrictions throughout 2020, engendered an unexpected and household-specific variation in savings rates. The estimated savings rate in 2020 ranges from 14.42% to 17.26%. These results sharply contrast with the estimated savings rate in 2019, ranging from 6,54% to 8.3%. Exploratory analysis indicates that this increase was also sustained in 2021. This, coupled with fluctuations in relative prices could influence other economic dimensions such as inequality and welfare.

References

- Battistin, Erich, Agar Brugiavini, Enrico Rettore, and Guglielmo Weber. 2009. "The Retirement Consumption Puzzle: Evidence from a Regression Discontinuity Approach." American Economic Review, 99 (5): 2209-26.

- Carvalho, V. M., Garcia, J. R., Hansen, S., Ortiz, Á., Rodrigo, T., Rodríguez Mora, J. V.and Ruiz, J. (2020) Tracking the COVID-19 Crisis with High-Resolution Transaction Data. Cambridge Working Papers in Economics CWPE2030

- Cavallo, A 2020. "Inflation with Covid Consumption Baskets," NBER Working Papers 27352, National Bureau of Economic Research, Inc

- Callaway B and Sant'Anna, P 2021. "Difference-in-Differences with multiple time periods", Journal of Econometrics, Volume 225, Issue 2, 200-230.

- Crespo, L., Gómez-García, M., Jovell, P., Rivera, B., Villanueva, E. (2023). "Pérdidas de ingresos y de empleo durante la pandemia de COVID-19 y situación financiera de los hogares: evidencia de la EFF". Boletín Económico 2023/T4, Banco de España.

- Deaton Angus S. & John Muellbauer 1980. Economics and Consumer Behavior. Cambridge University Press. Cambridge Mass.

- Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design. Econometrica, 69(1), 201–209.

- Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. Econometrica, 47(1), 153–161.

- Heckman, James J. "The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models." Annals of economic and social measurement, volume 5, number 4. NBER, 1976. 475-492.

- Hodbod, Alexander & Hommes, Cars Huber, Stefanie J. Salle, Isabelle, 2021. "The COVID-19 consumption game-changer: evidence from a large-scale multi-country survey," Working Paper Series 2599, European Central Bank.

- Janssen Meike, Chang Betty P. I., Hristov Hristo, Pravst Igor, Profeta Adriano, Millard Jeremy, 2021, "Changes in Food Consumption During the COVID-19 Pandemic: Analysis of Consumer Survey Data From the First Lockdown Period in Denmark, Germany, and Slovenia", Frontiers in Nutrition, 8.

- Jones, A.M. (1989), A double-hurdle model of cigarette consumption. J. Appl. Econ., 4: 23-39.

- Marianne Bertrand, Esther Duflo, Sendhil Mullainathan, How Much Should We Trust Differences-In-Differences Estimates?, The Quarterly Journal of Economics, Volume 119, Issue 1, February 2004, Pages 249–275.

- Navarro-Pérez, C.F., Fernández-Aparicio, Á., González-Jiménez, E. et al. Effects of COVID-19 lockdown on the dietary habits and lifestyle in a population in southern Spain: a cross-sectional questionnaire. Eur J Clin Nutr 76, 883–890 (2022).

- Pohlmeier W, Ulrich V. An econometric model of the two-part decision making in the demand for health care. J Human Res 1995; 30: 339–361.

- Prais, S. (1958), "Whose cost of living", Review of Economic Studies 26, 126.134.

- Cebada Romero, Alicia; Dominguez Redondo, Elvira, 2021. "Spain: One Pandemic and Two Versions of the State of Alarm", VerfBlog,

- Santos-Silva JMC, Windmeijer F. Two-part multiple spell models for health care demand. IFS WP Series No. W99/2, 1999.

- Scott R. Baker & R.A. Farrokhnia & Steffen Meyer & Michaela Pagel & Constantine Yannelis, 2020. "How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic," NBER Working Papers 26949, National Bureau of Economic Research, Inc.

- Solé B, Verdolini N, Amoretti S, Montejo L, Rosa AR, Hogg B, Garcia-Rizo C, Mezquida G, Bernardo M, Martinez-Aran A, Vieta E, Torrent C. Effects of the COVID-19 pandemic and lockdown in Spain: comparison between community controls and patients with a psychiatric disorder. Preliminary results from the BRIS-MHC STUDY. J Affect Disord. 2021 Feb 15;281:13-23.

Appendix

Table A1: Mean over treatment RDD (2020 wave of the EPF)

Variable	(1) Control	(2) Treated	(3) P-Value
Age	56.54	56.55	.999
Education Level 1-2	17.51%	15.93%	.129 (Joint)
Education Level 3-4	47.13%	47.34%	
Education Level 5-6	18.72%	20.43%	
Education Level 7-8	16.64%	16.26%	
Dependent Child	0.597	0.585	0.456
Number of Active Members	1.01	1.01	.0765
Teen Members	0.44	0.41	.02
Adult Members	1.62	1.66	.03
Elderly Members	0.514	0.504	.42
Log Income	5.41	5.39	0.215
N	4604	14566	

Table A2: Mean over treatment, 1 month span (2020 wave of the EPF)

Variable	(1) Control	(2) Treated	(3) P-Value
Age	55.51	57.11	.006
Education Level	4.16	3.99	.013 (Joint)
Dependent Child	0.635	.598	0.347
Number of Active Members	1.07	.099	.046
Teen Members	0.49	0.42	.014
Adult Members	1.73	1.65	.098
Elderly Members	0.46	0.51	.059
Log Income	5.41	5.33	0.00
N	1077	1458	

Table A3: Mean over treatment, 2 months span (2020 wave of the EPF)

Variable	(1) Control	(2) Treated	(3) P-Value
Age	56.04	57.07	.048
Education Level	4.14	4.11	0.376(Joint)
Dependent Child	0.636	.615	0.374
Number of Active Members	1.03	1.92	.612
Teen Members	0.474	0.448	.20
Adult Members	1.68	1.65	.2949
Elderly Members	0.497	0.524	.158
Log Income	5.41	5.37	0.006
N	3114	3319	

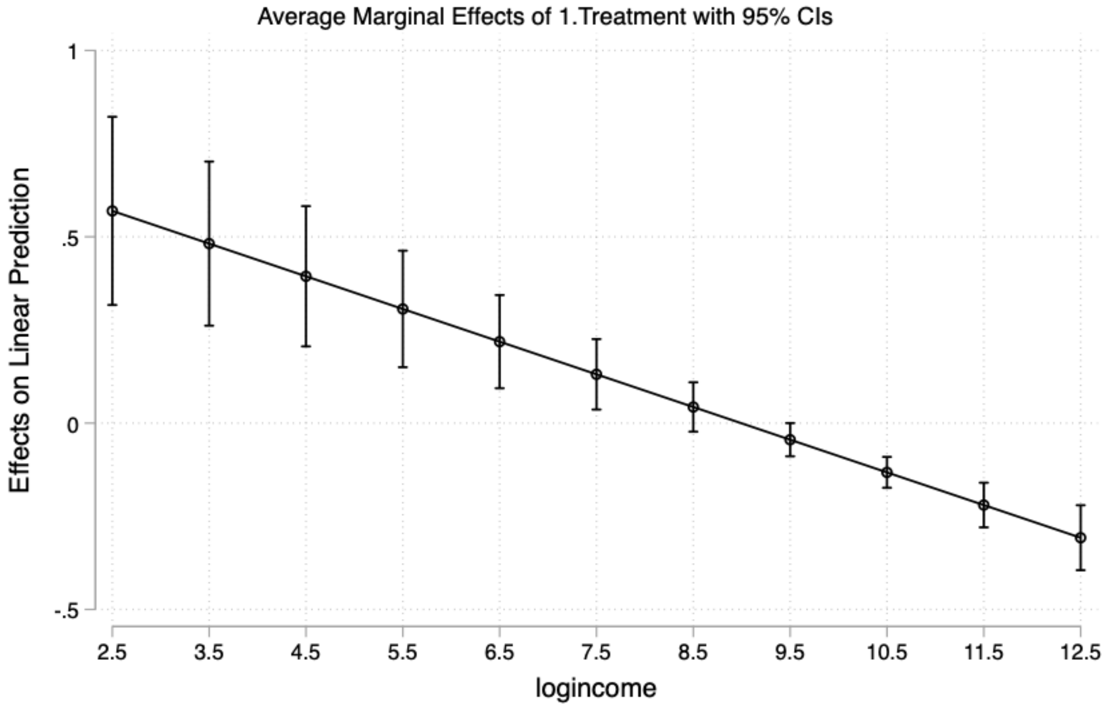

Figure A1: Treatment effect on total expenditure by income group (2020 wave of the EPF)

Table A4: Interacting Treatment and Total Expenditure (2020 wave of the EPF)

	Total	Food	Transport	Lamb	Services
DID	-.096***	.085***	-.477***	.747***	-.296***
	(.020)	(.025)	(.064)	(.134)	(.027)
Treatment	.163***	-.346	-.390	.315	.177
	(.054)	(.23)	(.582)	(1.04)	(.254)
Treatment × Exp	-.088***	.026*	-.005	.026	-.028*
	(.017)	(.014)	(.034)	(.062)	(.015)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: ATT estimates using equivalent income (2020 wave of the EPF)

	Total	Food	Transport	Lamb	Services
DID_{ws}	-.120***	.060**	-.575***	.698***	-.362***
	(.019)	(.028)	(.071)	(.135)	(.032)
N	14514	14401	12573	7051	14508
RDD_{ws}	-.113***	.039***	-.491***	.630***	-.269***
	(.008)	(.012)	(.031)	(.055)	(.014)
N	18441	18244	15503	9100	18430

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$