The dietary impact of the COVID-19 pandemic

Martin O'Connell, Kate Smith and Rebekah Stroud

University of Wisconsin-Madison & Institute for Fiscal Studies

$23/24^{th}$ September 2021

Motivation

The pandemic has had a major impact on the food (and drinks) market

- Disruptions to supply and access
- Hospitality sector shut-downs
- Changes in work patterns

Motivation

The pandemic has had a major impact on the food (and drinks) market

- Disruptions to supply and access
- Hospitality sector shut-downs
- Changes in work patterns

Many papers document big changes in consumer spending

- In UK: Hacioglu et al. (2020), Chronopoulos et al. (2020), Davenport et al. (2020), O'Connell et al. (2020) ...
- In US: Alexander and Karger (2020), Baker et al. (2020), Chetty et al. (2020), Cox et al. (2020) ...
- Elsewhere: Anderson et al. (2020), Carvalho et al. (2020), Chen et al. (2020) ...

Motivation

How, and to what extent, the spending changes have impacted dietary health will be one important determinant of the pandemic's long-run effect

Obesity and diet-related disease pose a major public health challenge

- Has the pandemic exacerbated this challenge?

Some small scale surveys suggest the answer may be yes

- American Psychological Association (2021), Public Health England (2021), Lin et al. (2021)

This paper

We quantify the impact of the pandemic on households' diets

Combine information from multiple sources, including

- Household scanner data that tracks food brought into home
- Out-of-home survey that tracks foods eaten outside the home (includes restaurants and takeaways)
- Both include information pre-pandemic up until the end of 2020

This paper

We quantify the impact of the pandemic on households' diets

Combine information from multiple sources, including

- Household scanner data that tracks food brought into home
- Out-of-home survey that tracks foods eaten outside the home (includes restaurants and takeaways)
- Both include information pre-pandemic up until the end of 2020

We show

- Pandemic led to big changes in where calories were purchased, and in the overall level of purchases
- These likely reflect changes in consumption
- And have important implications for population obesity levels

Main datasets

1. Kantar FMCG Purchase Panel
   - Covers purchases from grocery stores and online for "at-home" consumption
2. Kantar Out-of-Home Survey
   - Covers purchases from grocery stores for "out-of-home" consumption, plus those from restaurants and takeaway outlets
3. Living Costs and Food Survey
   - Covers all food and drinks
   - But cross-sectional and not available over pandemic

Kantar at-home data

- Covers purchases of all food and non-alcoholic drinks for at-home consumption
- January 2019-December 2020
- Panel members use electronic scanners to record all products at the UPC level
- Observe quantities and nutritional composition of products
- Sample contains 21,000 households observed, on average, for 21 months

Kantar out-of-home data

- Covers purchases of all food and non-alcoholic drinks for out-of-home consumption
  - Includes restaurants, takeaways, school, workplace, shops
- January 2019-December 2020
- Participating individuals (aged 13 or above) are randomly drawn for at-home data households
- Use a mobile phone app to record purchases
- Observe expenditure and detailed descriptions, but not nutrients
- Sample contains 5,000 households, observed, on average, for 20 months
  - Observe subset of individuals in each household

Data validation

1. Kantar at-home vs LCFS, 2011-2018 ▸ Details

2. Kantar data vs financial transaction data, 2019-2020 ▸ Details

Living Costs and Food Survey (LCFS)

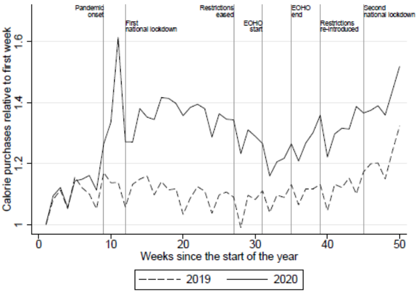
- Repeated cross-section of households, that includes two-week food diary
- Covers food consumed in and out of the home
- We use 2018; sample of 5500 household

Two main purposes:

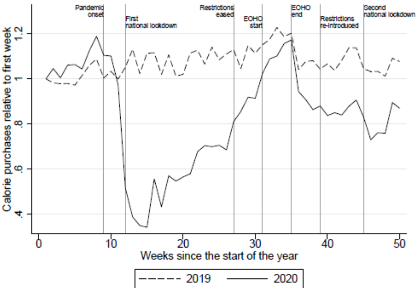
- Measure expenditure per calories of different out-of-home foods
- Measure pre-pandemic share of at-home and out-of-home food

Aggregate patterns

(a) At-home calories



(b) Out-of-home calories



Estimate dietary impact of the pandemic

1. Estimate impact of pandemic on at-home and out-of-home food separately

2. Combine together, with LCFS, to obtain estimate of impact on overall dietary health

Estimating changes in dietary components

y_{itm} is dietary outcome of interest of household i in month m of year t; using data for 2019–2020 we estimate

$$y_{itm} = \sum_{m=1}^{13} (\alpha_m + \beta_m \times 1[t = 2020]) + \lambda' X_{it} + \eta_i + e_{itm}$$

α_m capture seasonality
β_m capture mean change in y in m in 2020 relative to 2019
  β_m for $m > 2$ capture impact of pandemic
X_{it} are time-varying demographics
η_i are fixed effects

Measure percent change as:

$$\widehat{\Delta y}_m \equiv \hat{\beta}_m / \mathbb{E}(\tilde{y}_{itm} | m)$$

where $\tilde{y}_{itm}$ is predicted y excluding pandemic dummies

Estimating change in overall diet

Let y_{imt}^{in} and y_{imt}^{out} denote a dietary measure (e.g. calories) in and out, where

- $t = 1$ corresponds to pandemic; $t = 0$ is absence of pandemic
- $y_{imt}^{tot} = y_{imt}^{in} + y_{imt}^{out}$

Note:

$$\begin{aligned}\Delta y_{im}^{tot} &= \frac{y_{im1}^{tot} - y_{im0}^{tot}}{y_{im0}^{tot}} \\ &= \Delta y_{im}^{in} w_{im} + \Delta y_{im}^{out}(1 - w_{im})\end{aligned}$$

where $w_{im} = \frac{y_{im0}^{in}}{y_{im0}^{tot}}$

Using $\Delta y_{m}^{in} = \mathbb{E}(\Delta y_{im}^{in})$, $\Delta y_{m}^{out} = \mathbb{E}(\Delta y_{im}^{out})$ and $\bar{w}_m = \mathbb{E}(w_{im})$ would ignore important correlations

3 step approach

1. Use LCFS to estimate flexible (double-hurdle) model of how w_{im} varies with
   - Demographics (SES, no of adults, no of children, age, region)
   - Quintile of at-home calories distribution
   - Month of year

   Use estimates to predict $\hat{w}_{im}$ for households in Kantar data

2. For each of 135 demographic cells, d, estimate at- and out-of-home effect:

$$\widehat{\Delta y}^{in}_{m,d} = \frac{\hat{\beta}^{in}_{m,d}}{\mathbb{E}(\tilde{y}_{itm}|m,d)}, \qquad \widehat{\Delta y}^{out}_{m,d} = \frac{\hat{\beta}^{out}_{m,d}}{\mathbb{E}(\tilde{y}_{itm}|m,d)}.$$

3 step approach

3. Combine to obtain estimate of total effect:

$$\widehat{\Delta y}_m^{tot} = \sum_d s_{m,d} \left(\widehat{\Delta y}_{m,d}^{in} \hat{w}_{m,d} + \widehat{\Delta y}_{m,d}^{out} (1 - \hat{w}_{m,d}) \right).$$

Identification and model fit

Three key assumptions that we make

1. In absence of pandemic dietary outcomes would have evolved in 2020 similarly to 2019

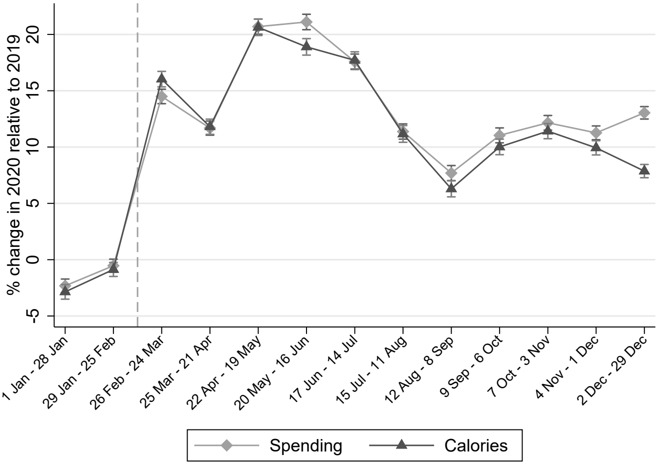
2. Predicted shares based on 2018 estimates are a valid counterfactual for absence of pandemic shares in 2020

3. The 135 demographic cells are sufficiently detailed to capture household-level correlations

▸ Details

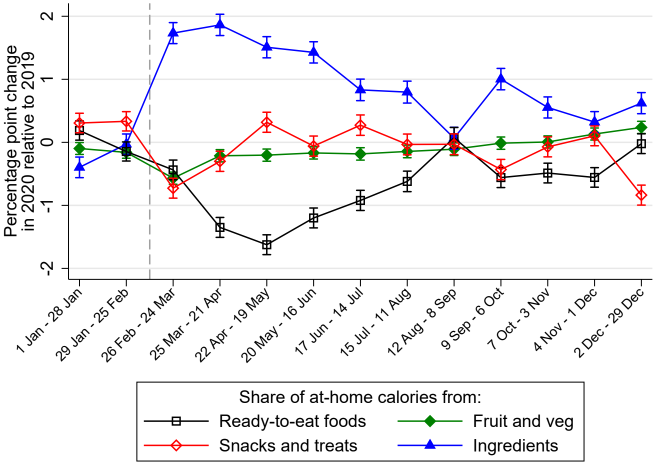
Change in at-home diet

Calories



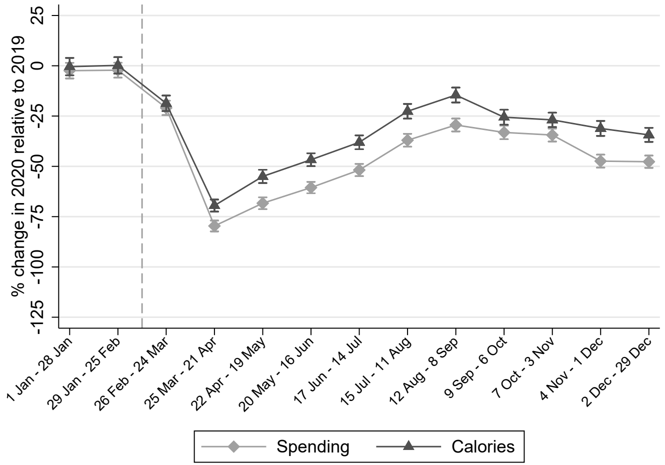
Change in at-home diet

Composition of calories



Change in out-of-home diet

Calories

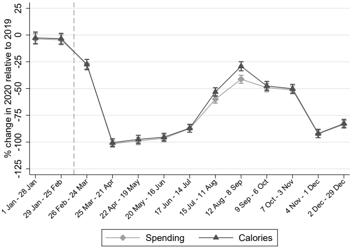


▸ Placebo

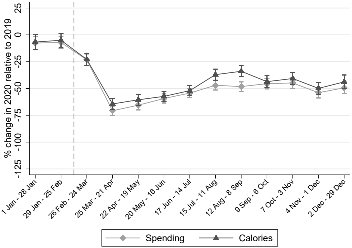
Change in out-of-home diet

Calories, by outlet type

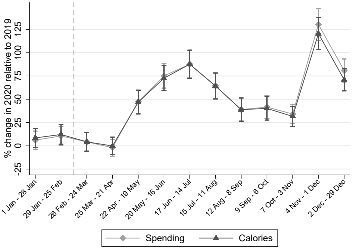
(a) Dine-in restaurants



(b) On-the-go

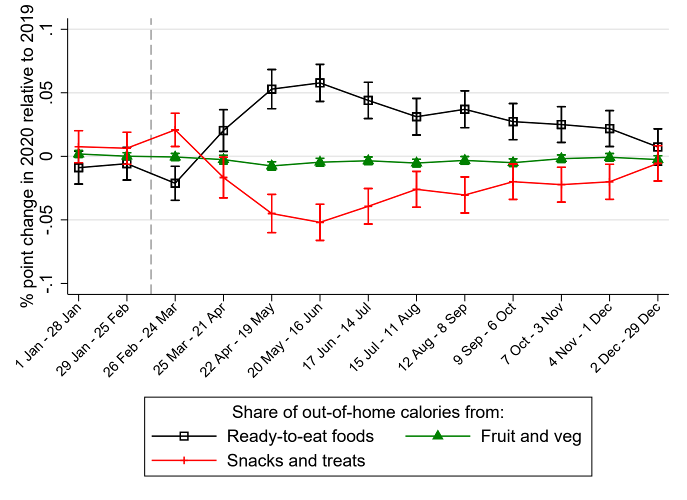


(c) Takeaways



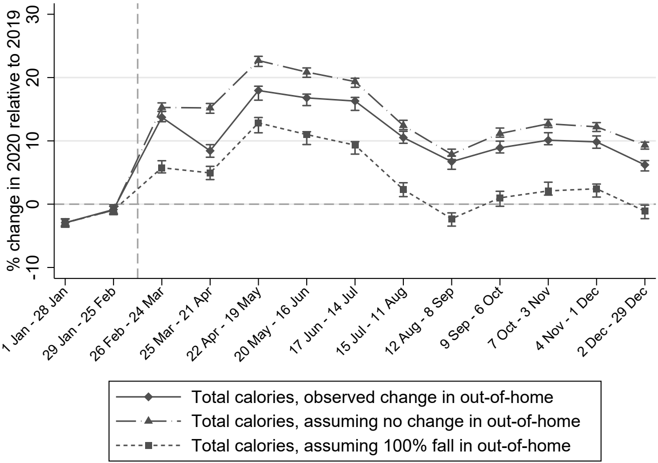
Change in out-of-home diet

Composition of calories



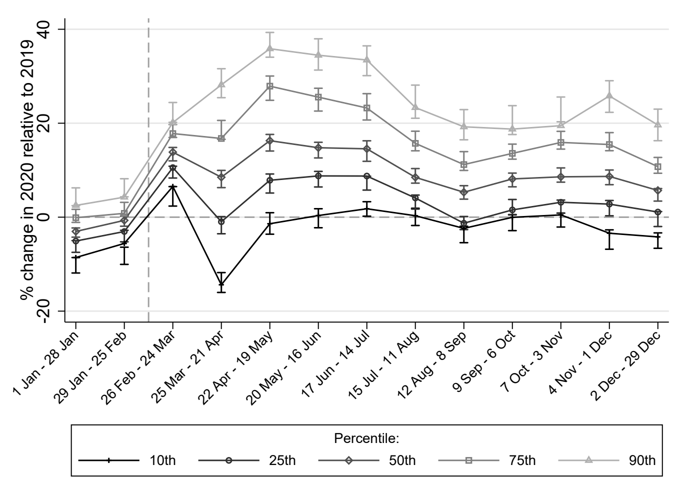
Change in overall diet

Calories, mean



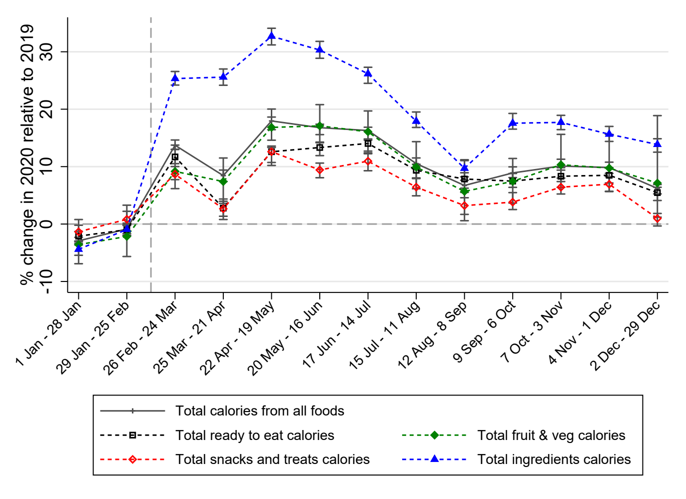
Change in overall diet

Calories, distribution



Change in overall diet

Composition of calories



Summary

Pandemic led to

- Sustained increase in at-home calories (20% in May, 10% in Dec)
- Increase in share of at-home ingredient calories

Summary

Pandemic led to

- Sustained increase in at-home calories (20% in May, 10% in Dec)
- Increase in share of at-home ingredient calories
- Fall in out-of-home calories (70% in May, 25% in Dec)
- Big fall in restaurants, partially off-set by takeaways
- Increase in share of ready-to-eat calories

Summary

Pandemic led to

- Sustained increase in at-home calories (20% in May, 10% in Dec)
- Increase in share of at-home ingredient calories

- Fall in out-of-home calories (70% in May, 25% in Dec)
- Big fall in restaurants, partially off-set by takeaways
- Increase in share of ready-to-eat calories

- Overall increase in calories (15% in May, 8% in Dec)
- Translate into 280, and 153 calorie p.ae.p.d increase Details
- Increase for 90% of distribution
- Increase in share of ingredients in total calories

Do purchase increases reflect higher consumption?

Alternative explanations, include

- Changes in household composition
  - Scale reported in UKHLS too small to play important role
- At-home food waste
  - Redo analysis assuming 15% at-home food waste; makes little difference
- Increases in households' stocks
  - Strong evidence of stocking up of storables in March, followed by temporary fall in storable purchases (O'Connell et al. (2020))
  - But calories increases persist over entire 2020

Implications for obesity levels

We match households in our data with those in Health Survey for England, by demographic cell

- Latter provides information on height and weight

We apply our calorie change estimates to a dynamic epidemiological model (Hall et al. (2011))

Consider two scenarios

- Calories revert back to normal early 2021
- Calorie increases are permanent

Implications for obesity levels

		If calories revert to normal in March 2021, level after:			If calories remain permanently higher
	Pre-pandemic	1 year	2 years	3 years	3 years
Mean BMI	27.5	28.9	28.2	27.7	29.7
% adults who are overweight	63.3	74.8	68.3	64.3	78.8
% adults who are obese	27.7	36.1	31.8	29.2	41.5

Will calorie increases be permanent?

Even if increase in calories is temporary, size and persistence of increase could have important implications for obesity

If increase is permanent implications are very large

Will calorie increases be permanent?

Even if increase in calories is temporary, size and persistence of increase could have important implications for obesity

If increase is permanent implications are very large

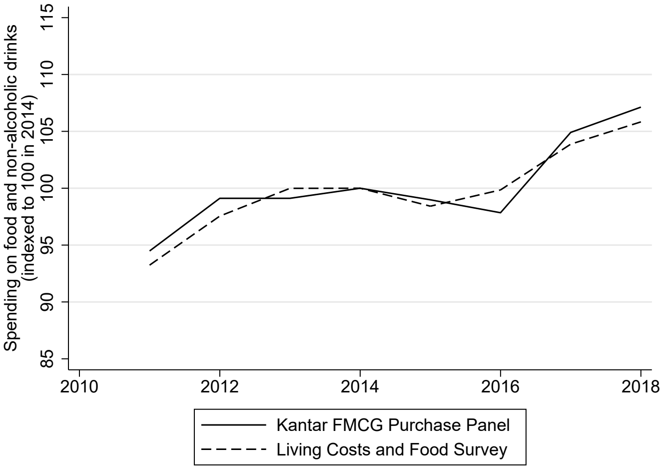
Remains an open question, but there is some suggestive evidence pointing in this direction

- Biggest calorie increases are among young (2 p.p. higher than those aged 40-60), high SES households (7 p.p. higher than lowest group), those based in London (3 p.p. higher)
- Same groups that seen biggest switch towards home working
- A change likely to outlast pandemic

Extra Slides

Kantar vs LCFS, 2011-2018

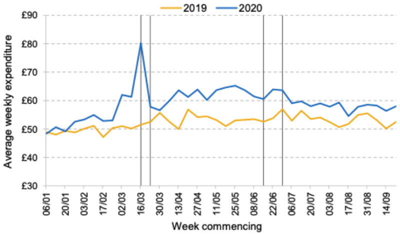
Back



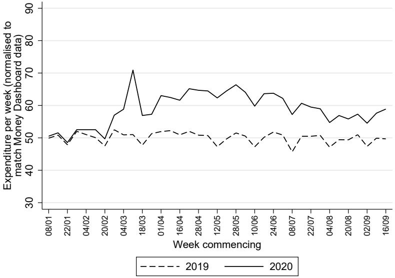
Kantar vs Money Dashboard

Back

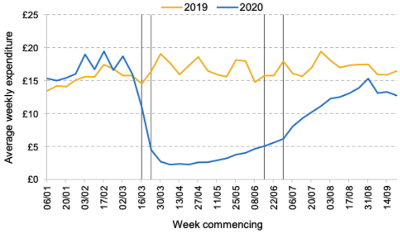
(a) Groceries: MDB



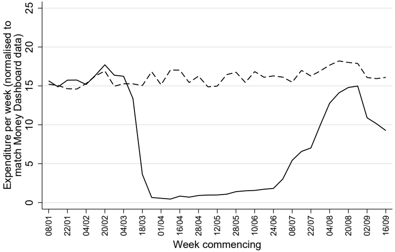
(b) Groceries: Kantar



(c) Dining out & recreation: MDB

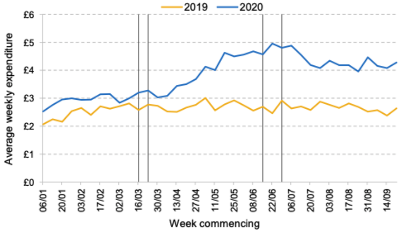


(d) Dining out: Kantar

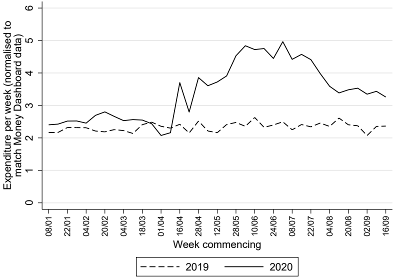


Kantar vs Money Dashboard ▸ Back

(e) Takeaways: MDB

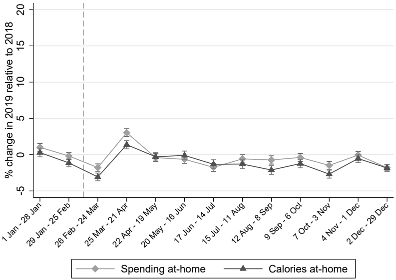


(f) Takeaways: Kantar

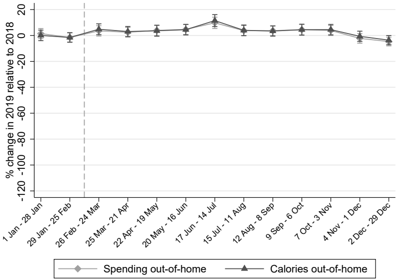


Placebo tests
Back

(a) At-home, 2018 to 2019



(b) Out-of-home, 2018 to 2019



Share of calories from at-home, LCFS data ▸ Back

	Mean	s.d.	p10	p25	p50	p75	p90
Stability across years							
2016	0.894	0.114	0.750	0.851	0.926	0.978	1.000
2017	0.894	0.115	0.750	0.849	0.926	0.978	1.000
2018	0.898	0.107	0.761	0.851	0.929	0.979	1.000
Fit of linear-hurdle model							
Observed	0.898	0.107	0.761	0.851	0.929	0.979	1.000
Predictions	0.900	0.072	0.785	0.861	0.904	0.946	1.000

Change in calories per adult equivalent per day over the pandemic

Back

	Calories from:				
	All food	Ready-to-eat	Ingredients	Snacks	Fruit & veg
March – July 2020	280	92	122	34	19
	[266, 284]	[84, 94]	[113, 129]	[30, 38]	[16, 23]
July - Dec 2020	153	65	56	15	11
	[144, 161]	[59, 70]	[53, 59]	[12, 19]	[6, 18]