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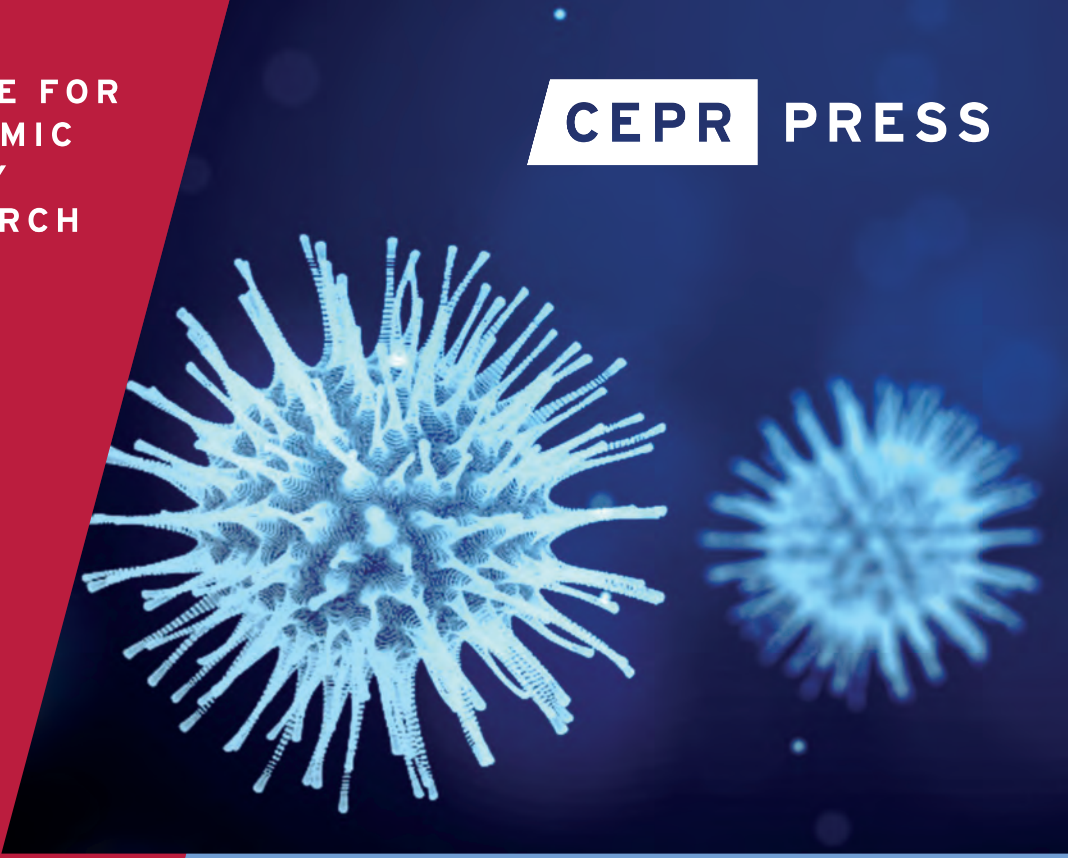

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 64
13 JANUARY 2021

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REVIEW OF SUPPORT MEASURES IN THE US
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Covid Economics
Vetted and Real-Time Papers

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Ethics

Covid Economics will feature high quality analyses of economic aspects of the health crisis. However, the pandemic also raises a number of complex ethical issues. Economists tend to think about trade-offs, in this case lives vs. costs, patient selection at a time of scarcity, and more. In the spirit of academic freedom, neither the Editors of *Covid Economics* nor CEPR take a stand on these issues and therefore do not bear any responsibility for views expressed in the articles.

Submission to professional journals

The following journals have indicated that they will accept submissions of papers featured in *Covid Economics* because they are working papers. Most expect revised versions. This list will be updated regularly.

American Economic Review
American Economic Review, Applied Economics
American Economic Review, Insights
American Economic Review, Economic Policy
American Economic Review, Macroeconomics
American Economic Review, Microeconomics
American Journal of Health Economics
Canadian Journal of Economics
*Econometrica**
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Economics of Disasters and Climate Change
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Journal of Public Finance and Public Choice
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Journal of Population Economics
Quarterly Journal of Economics
*Review of Corporate Finance Studies**
Review of Economics and Statistics
*Review of Economic Studies**
Review of Financial Studies

(*) Must be a significantly revised and extended version of the paper featured in *Covid Economics*.

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Zoomshock: The geography and local labour market consequences of working from home[1]

Gianni De Fraja,[2] Jesse Matheson[3] and James Rockey[4]

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The Covid-19 health crisis has led to a substantial increase in work done from home, which shifts economic activity across geographic space. We refer to this shift as a 'Zoomshock'. The Zoomshock has implications for locally consumed services; the clientèle of restaurants, coffee bars, pubs, hair stylists, health clubs located near workplaces now demand those services near where they live. In this paper we measure the Zoomshock at a granular level for UK neighbourhoods. We establish three important empirical facts. First, the Zoomshock is large; many workers can work-from-home and live in a different neighbourhood than they work. Second, the Zoomshock is very heterogenous; economic activity is decreasing in productive city centres and increasing residential suburbs. Third, the Zoomshock moves workers away from neighbourhoods with a large supply of locally consumed services to neighbourhoods where the supply of these services is relatively scarce. We discuss the implications for aggregate employment and local economic recovery following the Covid-19 pandemic.

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1 We gratefully acknowledge financial support from UK Research and Innovation and the Economic and Social Research Council (ESRC grant number ES/V004913/1). A supplementary online appendix is available at https://perma.cc/P6RR-NMW4.

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1 Introduction

A defining feature of modern life is the office. And the concentration of offices in city centres and business parks has meant commuting is a fact of life for many workers. As the lot of a commuter is to spend much of their time away from home, their consumption reflects that. Workers buy sandwiches for lunch, coffee during breaks, and after-work drinks. They also visit retail shops near their offices, have their hair cut between meetings, visit gyms before work, they use taxis, have their car serviced while they are in the office, and so on. These are all examples of locally consumed services (LCS): these are services defined by necessarily being supplied and demanded in a given place.

The Covid-19 pandemic has led to an unprecedented shift in the fraction of work that is done from home versus the office. This geographic shift in productive activities, which we refer to as the *Zoomshock*, moves work and workers from their offices in high density urban areas to comparatively low density residential neighbourhoods. This has had important consequences for providers of LCS. Establishments previously patronised by commuters are suffering, while neighbourhood establishments have seen a surge in demand from homeworkers.

This paper has two objectives. First, we propose an empirical measure of the Zoomshock. This metric reflects the change in of work activities (measured as the number of employees or total income) for a given neighbourhood. It weights the difference between workers who work and live in a given neighbourhoods by their ability to work-from-home. We use this method to estimate Zoomshocks for each neighbourhood in England, Scotland and Wales. A clear pattern emerges: the Covid-19 Zoomshock has moved productive activity away from formerly highly output city centres into residential areas.

Second, we examine the consequences of the Zoomshock for LCS in the affected neighbourhoods and employment in the larger industry. In the short to medium-run the Zoomshock creates a geographic supply-demand mismatch; there are many LCS businesses in city centres but relatively few in the residential suburbs. Even when we allow for perfect mobility of labour, the fact that capital is slow to move, and the lack of density in the suburbs, means that LCS employment will fall below its pre-Covid-19 level.

We believe that the concept of Zoomshock will prove useful for deigning policy that seeks to minimise the economic damage caused by the Covid-19 pandemic, and to use scarce resources devoted to economic recovery as efficiently as possible. Although preliminary, several implications are clear from our analysis. First, at the local level there is very significant geographic heterogeneity within urban areas in how working from home will impact LCS businesses. Any recovery assistance policy should reflect this heterogeneity and focus resources on firms and workers in neighbourhoods who have experienced a negative Zoomshock. Second, the aggregate consequences across neighbourhoods of the Zoomshock will be in larger in some areas. Local authorities where the skewness of the neighbourhood-level Zoomshock distribution is greater are likely to suffer a greater employment loss in the LCS industry. Finally, it is critical that we understand better the long-run consequences of the Zoomshock. The efficient policy prescription will depend crucially on how many former commuters continue to work-from-home once the Covid-19 pandemic subsides. If the switch to working-from-home is permanent for at least some of the work-

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ers, for at least some of the time, it may portend long-lasting changes in the productive structure of localised areas: 50% of the commuters to an area switch to working-from-home for two days per week is a 20% loss in potential demand for the area LCS. In the long term, establishments providing LCS may drift from the high streets to the suburbs.

It should be stressed that we do not attempt to fully capture the effect of the Covid-19 pandemic on the LCS industry. This industry has been hit particularity hard by social distancing measures, and will undoubtedly be negatively impacted if the broader economy struggles to recover following the pandemic. Here we abstract from these effects of the pandemic, both for LCS and the broader labour market, and focus on how homeworking specifically will impact these businesses. These consequences, and the implications for recovery policy, are have not yet been studied but the potential implications of working-from-home for the recovery of employment and output in the wake of the Covid-19 pandemic are, as we will see, of first-order importance.

This paper complements empirical studies that look at the regional geography of economic risks arising from the Covid-19 pandemic (Davenport et al., 2020). We emphasise the importance of working with relatively small areas: in theory, and as we will empirically demonstrate, a small local area may be severely affected by the Zoomshock while neighbouring areas potentially benefit from the shock. Zoomshocks are also very complex: they depend on (i) commuting patterns: these are highly asymmetric, most commuters travel from "residential areas" in cities, the suburbs, or the countryside to work in city-centres; (ii) the ability of commuters to work remotely: office workers with little contact with customers can work-from-home easily, vets and events managers

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with greater difficulty if at all; (iii) commuters' demand for LCS: this in turn depends on both the commuters' income and the fraction they spend on LCS— expensive wine bars are LCS, but home delivery of cases of fine wine is not, and how much of the LCS are consumed at work— the services supplied by gardeners and nannies are by their nature not consumed at the work location. (iv) and finally on the ability of supply to adjust to increased demand: a community with many home-working residents may find that some continue to demand similar LCS as when they commuted, e.g. they may still prefer to buy their lunch, rather than prepering it themselves. But existing businesses might be unable to increase their supply to satisfy this demand.

This paper contributes to an emerging evidence base on the costs, in labour market terms, of stay at home orders. Baek et al. (Forthcoming), provides evidence that stay at home account for less than a quarter of total Covid related job losses in the US. But this impact has been uneven. Crossley et al. (2021), using panel data for the UK, find that the impacts of the pandemic have been most pronounced for those on the lowest incomes, and those from minority ethnic groups. Mongey and Weinberg (2020) find similar results for the US. Angelucci et al. (2020) also find that health losses are disproportionately concentrated on these groups. Barrero et al. (2020) suggest that 42% of jobs lost due to Covid in the US will be permanent.

It also contributes to a second strand of the post-Covid literature whose focus is on which, and how many, jobs can be done from home. Dingel and Neiman (2020) provided early U.S. and international evidence. Alipour et al. (2020) provide similar evidence for Germany. In this paper we add to this literature by proposing a classification for the UK, and mapping occupation and

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wage heterogeity in ability to work-from-home to geographic heterogeneity. Gottlieb et al. (2020) study what share of jobs are tele-workable across countries, documenting that fewer jobs are tele-workable in lower income countries, in part due to the higher share and nature of self-employment in those countries.

Others have documented the impact on consumption patterns (Baker et al., 2020; Barrero et al., 2020; Chronopoulos et al., 2020). To our knowledge there has been little attention to the spatial aspects of these changes.

This is one of the few papers to consider the spatial aspects of working-from-home. In contemporaneous work Delventhal and Parkhomenko (2020) provide a quantitative model for Los Angeles to study how in the long-run teleworking may affect the spatial distribution of jobs and residents. In another contemporaneous contribution Delventhal et al. (2020) introduce a quantitative spatial equilibrium model in which workers are heterogeneous in the amount of time they work "on site". Their model predicts a non-monotonic impact of teleworking—increasing activity in the most productive cities while also in the lowest density areas.

This paper proceeds as follows. In Section 2, we specify how we measure the Zoomshock, characterising it by geographic shifts in workers and geographic shifts in GDP. In Section 3 we discuss the data which we use in our primary analysis: this comes from the UK Annual Survey of Hours and Earnings. In Section 4 we use these measures to examine the Zoomshock across Britain, and how working-from-home has changed the geography of productive activities. In Section 5 we discuss, and provide some theoretical basis for, the impact that working from home has on the LCS industry at highly localised levels and on

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aggregate LCS employment. We conclude with some discussion of the outstanding information needed and implications for short and longer-term policy.

2 The Zoomshock

We use the term *Zoomshock* to describe the geographic change in economic activity due to the shift towards working-from-home during the Covid-19 pandemic. Here we present metrics that can be calculated using existing data and capture the differences in the sign and magnitude of the Zoomshock in different neighbourhoods. We consider two different ways of thinking about a change in economic activity. The first is by looking at the geographic change in the number of workers (which will be the focus of our empirical analysis). The second is by looking at the geographic change in GDP, measured as the income of these worker.

Consider first the change in the number of workers within a geographically defined zone, z. This change can be estimated by considering three characteristics: 1) the number of workers who work in z; 2) the number of workers who live in z; 3) and whether the jobs performed by these workers can be done at home. In plain English, we wish to calculate a metric, ζ_z, defined as:

$$\zeta_z = \begin{pmatrix} \text{weighted count of} \\ \text{workers who are resident} \\ \text{in zone } z \text{ and working} \\ \text{elsewhere: they } \textit{return to } z \end{pmatrix} - \begin{pmatrix} \text{weighted count of} \\ \text{workers who are working} \\ \text{in zone } z \text{ and resident} \\ \text{elsewhere: they } \textit{leave } z \end{pmatrix}, \quad (1)$$

where the weighting of the count is given by the measure of the ability to per-

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form their work at home. This is the difference between the number of workers who are able to leave zone z to work from their home located in zone $z' \neq z$, and the number of individuals who are resident in zone z and are able to work from home instead of having to go in person to zone $z'' \neq z$.

Formally, (1) can be calculated for each zone z as follows:

$$\zeta_z = \sum_i \mathbf{HD}_i' \left(\mathbb{1}[residence_i = z] - \mathbb{1}[work_i = z] \right), \tag{2}$$

where $\mathbb{1}[\cdot] \in \{0, 1\}$ is an indicator function. $\mathbb{1}[residence_i = z]$ equals 1 if individual i lives in zone z, and 0 otherwise; $\mathbb{1}[work_i = z]$ equals 1 if individual i works in zone z, and 0 otherwise. $\mathbf{H}$ and $\mathbf{D}_i$ are vectors of occupation-specific work-from-home indices and individual i's occupation, respectively.

The product $\mathbf{HD}_i' \in [0, 1]$ is worker i's work-from-home index, with which we weight each observation. We adapt the home-working classification of Dingel and Neiman (2020) for each of our 380 four-digit UK Standardised Occupation Codes, with minor adjustments required to map US job descriptions to the UK ones. Formally, given a set of occupations $o = 1, \ldots, 380$, $\mathbf{H} = (h_1, h_2, ..., h_{380}) \in [0, 1]^{380}$ is a vector of occupation-specific indices for which an element $h_o \in [0, 1]$ reflects the feasibility of performing the duties required by occupation o in a location other than "work". A delivery driver will generally have a home-working index of $h_o = 0$, an IT software consultant will have an index of $h_o = 1$. Other workers may have an intermediate value, as they can perform some tasks remotely, but some require their physical presence.[1]

[1] As examples of occupations with an index of 0.5, forklift truck drivers, artists, and credit controllers are among them. For security guards, the index is $\frac{1}{3}$, for estate agents $\frac{3}{4}$, and for garage managers and proprietors $\frac{8}{9}$: of the 380 4-digit occupation classified by the ONS, 162 are

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$\mathbf{D}_i \in \{0,1\}^{380}$ is a vector of occupation dummies for individual i's main job, that is a vector whose o-th element is 1 if and only if occupation o is individual i's main job.

Our resulting work-from-home index matches well with data reflecting actual working from home (see `https://perma.cc/P6RR-NMW4` for analysis). We also find that workers who can work from home are paid more (this corresponds to Aum et al. (2020) for the US): controlling for industry, year, age, hours worked, gender, and region of residence, a worker who can work from home is paid over 40% more that one who cannot.

Expression (2) has a number of properties worth pointing out. First, occupations which cannot be done at home, such as those in the LCS industry, will not change the values of ζ_z; occupations for which $h_o = 0$ carry no weight. Second, ζ_z reflects the economic activity of those who commute in or out of zone z; individuals who work and live in the same zone will not affect (2). Third, ζ_z aggregates to higher levels of geographic space. For any geographic area made up of multiple non-overlapping zones, denote this $A = \{z_1, z_2, ..., z_n\}$, we can calculate:

$$\zeta_A = \sum_{z \in A} \sum_i \mathbf{H}\mathbf{D}_i' \left(\mathbb{1}[residence_i = z] - \mathbb{1}[work_i = z]\right). \tag{3}$$

When areas or zones vary considerably in population, as is the case with British local authorities, it will prove convenient, for the sake of comparison, to work also with a per capita Zoomshock: this is obtained by dividing the RHS of Ex-

classified as not suitable for home-working, 124 as partly suitable, and 94 as fully suitable. We provide a descriptive analysis of our resulting work-from-home index in the online Appendix (`https://perma.cc/P6RR-NMW4`).

pression (3) by the number of pre-shock workers in area A.

$$\widehat{\zeta}_A = \frac{\sum_{z\in A}\sum_i \mathbf{HD}'_i\left(\mathbb{1}[residence_i = z] - \mathbb{1}[work_i = z]\right)}{\sum_{z\in A}\sum_i \mathbb{1}[work_i = z]} \times 100. \tag{4}$$

Expression (4) is percentage change in employment activities in area A. $\widehat{\zeta}_A$ can also be calculated for a specific zone, z, as a special case where $A = \{z\}$.

The above expressions look at the change in the number of workers across geography due to a shift to working from home. It is also useful to measure changes in economic activity in terms of the change in the value of output produced in a specific area. To do this we weight equations (3) and (4) by income for each individual i, which we denote by y_i.[2] This gives us

$$\zeta_A^y = \sum_{z\in A}\sum_i \mathbf{HD}'_i y_i\left(\mathbb{1}[residence_i = z] - \mathbb{1}[work_i = z]\right), \tag{5}$$

and

$$\widehat{\zeta}_A^y = \frac{\sum_{z\in A}\sum_i \mathbf{HD}'_i y_i\left(\mathbb{1}[residence_i = z] - \mathbb{1}[work_i = z]\right)}{\sum_{z\in A}\sum_i \mathbb{1}[work_i = z]} \times 100. \tag{6}$$

[2] A substantial recent literature has studied the efficiency of working from home. Bloom et al. (2015) provide evidence from a within-firm RCT that homeworking increases the productivity of call-centre workers by up to 22%. Mas and Pallais (2017) find that the average call-centre worker is willing to pay 8% to work from home. Although, Battiston et al. (Forthcoming) provides evidence that face-to-face communication improves productivity. One reading of these somewhat contradictory results is that the optimum level of working-from-home is some mix of office- and elsewhere-based work. Here, we assume there is no aggregate impact on the productivity of those working-from-home. We also abstract from other consequences of work flexibility (Kelly et al., 2014; Allen et al., 2015; Beckmann et al., 2017; Felstead and Henseke, 2017; Spreitzer et al., 2017; Chan, 2018; Ameriks et al., 2020).

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3 Data

We calculate the expressions on the RHS of (2) and (3) using information from the secure version of the *Annual Survey of Hours and Earnings* (ASHE). The ASHE contains a random 1% sample of all employees in England, Wales, and Scotland.[3] In addition to detailed occupation and earnings information, we also observe the precise geographic location of employment and residence for each individual in our data. We construct pre-Covid-19 employment distributions using the 2017, 2018 and 2019 waves of the data. This provides us with observations on approximately $200,000$ workers.

We conduct our analysis at the level of the *Middle Super Output Area* (MSOA) for England and Wales and *Intermediate Zone* for Scotland (for brevity we refer simply to MSOA hereafter). These are areas of roughly the same residential population size (the mean population is around 9000 people).[4] We also consider a second, coarser, geographical partition, the Lower Tier Local Authority (LAD).[5] These are administrative and political units, and vary substantially in size. The largest, Birmingham has a population of over 1 million while the Isles of Scilly a population of just over $2,000$.

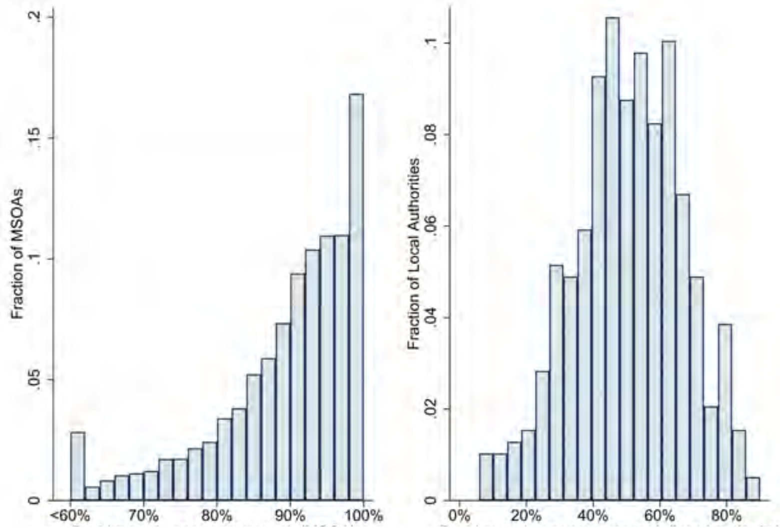
Only 11% of UK workers have the home and the work address in the same MSOA, and there is considerable variation in this proportion across the coun-

[3]Unfortunately, data for the ASHE, required for our analysis, is not available for Northern Ireland.

[4]In principle it would be possible to work with even finer geographies but MSOAs are preferred since they are large enough that they will in general represent a local community with some shops, etc., rather than just a collection of houses. Smaller areas would also ask too much of the data.

[5]Specifically, we analyse the Local Authority Districts in England, the Council Areas in Scotland, and the Principal Areas in Wales.

Figure 1:
Commuters by MSOA and Local Authority



Note: The horizontal axis is the percent of residents who work outside of the MSOA (left) and LAD (right) in which they live.
Data source: Authors' calculations based on data from the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019.

try. In Figure 1 we show the distribution, across all MSOAs, in the proportion of workers who live and work in different MSOAs (i.e. commuters). Clearly, the role of commuting is a significant; in over 97% of MSOAs more than 60% of residents commute for work (Figure 1, left panel). One naturally expects that the proportion of commuters will decrease as the area we look at is larger, but the proportion of commuters remains significant when we look at local authorities: around 50% of workers commute to a different local authority than that in which they live (Figure 1, right panel). Moreover, there is considerable varia-

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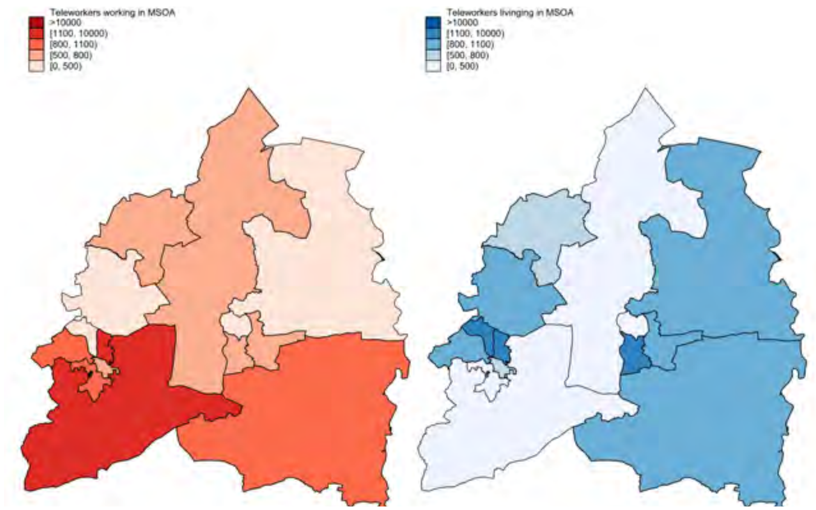
Figure 2:
Residents and workers who can work-from-home, Bassetlaw



Note: These maps show, for each MSOA, the number of workers who are resident in each MSOA and can work-from-home (left map), and the number of workers whose place of work is in the MSOA and can work-from-home (right map).
Data source: Authors' calculation based on data from the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019.

tion: some LADs have over three quarters of their residents working elsewhere, in others LADs fewer than one in five do so. Thus, commuting even between large areas is common and varies in extent.

4 Geography of the Zoomshock

As an illustration, we begin our analysis—like so many others—by considering Bassetlaw. This is a relatively small LAD, 150 miles north of London. There are 14 MSOAs in Bassetlaw; for each MSOA, we compute the number of em-

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ployed residents who can work from home: this is first term in Equation (1), and is depicted on the left map of Figure 2. We next compute the corresponding number of workers whose place of work is in an MSOA in Bassetlaw, but who can work-from-home in a different MSOA (possibly also in the Bassetlaw local authority): this is the second term in (2), and is depicted on the right map of Figure 2. The MSOA known as Bassetlaw 014 (the large dark red region on the left map of Figure 2) has approximately 1465 workers who live in the MSOA, but 5661 workers who work in the MSOA. Of the former, we compute that 485 workers can work-from-home, approximately one third. Of the latter, 1,828 can work-from-home, again just about a third. Therefore, if all workers who can work from home do so, we expect Bassetlaw 014 to see a net decrease in employment of approximately $1,828 - 485 = 1,343$ workers.

The maps in Figure 3 show the corresponding Zoomshock for each of the MSOAs in the Bassetlaw local authority. The map to the left of this figure illustrates the net inflow of homeworking workers (Equation (2)), and reflects the difference between the left and right maps of Figure 2. Red (blue) areas correspond to MSOAs in which home working results in less (more) economic activity, that is MSOA z for which (2) is negative (positive). The depth of the shades of red and blue corresponds to strength of the flow, a deeper shade indicates a larger flow. Boundary between colour bins are set, for positive and negative values separately, at Zoomshock values approximately at the 20th, 40th, 60th, 80th and 95th MSOA percentiles for Britain.

The right hand side map of Figure 3 reports the same exercise for Equation (5), so the Zoomshock reflects changes in the value of economic activity across MSOAs. This is different way of looking at the geographic shift in economic ac-

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tivity due to home-working, and roughly corresponds to the potential change in the annual GDP for a area z. Notice that quintile assignments of the two Bassetlaw maps in Figure 3 are roughly in agreement with one another, but there are differences, for example, there are two changes in the sign of the flow: one MSOA for which the change in the flow of workers is negative (positive), while the corresponding GDP change is positive (negative). An area with a negative net-flow of workers (a red shade on the LHS map) and a positive GDP net-flow (a blue shade on the RHS map) is one where the residents are relatively highly paid workers, and although those who stop commuting to work from home are fewer, they are sufficiently better paid on average to more than offset the incomes of the larger number of workers who no longer need come into the area to work. In the maps and analysis that follow, for brevity, we focus primarily on the Zoomshock in terms of workers, and leave the important analysis of income flows for future research.

The primary drivers of variation in the Zoomshock are the distribution of where people live relative to where they work, and the geographic clustering of work which is potentially suitable for home-working. We illustrate the second in Figure 4 for the Greater London Authority. The left-hand-side map shows the geographic distribution of all employment; the right hand side map shows employment weighted by the home-working index. The comparison between the two panels makes it clear that jobs suitable for home-working are disproportionately concentrated in the centre of London.

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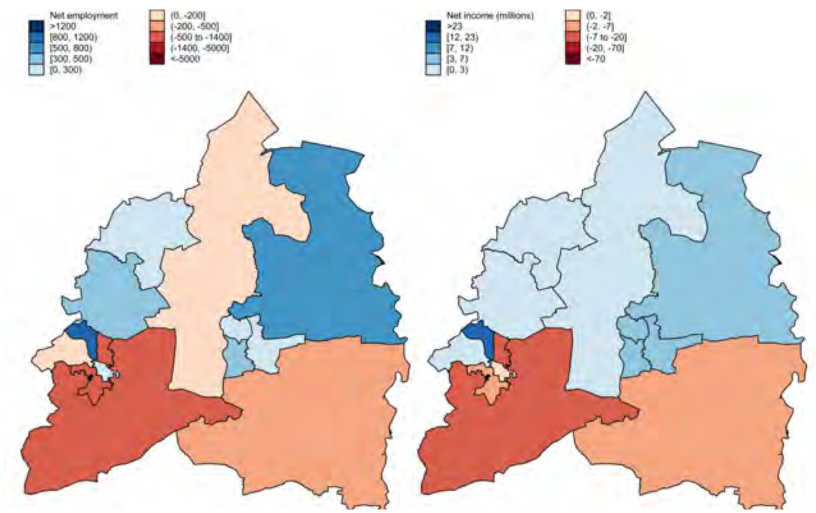
Figure 3:
Zoomshock by workers and GDP, Bassetlaw



Note: These maps show quantiles of expressions (2) and (5) by MSOA. Quantile boundaries are calculated separately for positive and negative shocks to represent the 25th, 50th, 75th, and 95th percentiles for Great Britain.
Data source: Authors' calculation based on data from the ONS *Annual Survey of Hours and Earnings*, 2017, 2018, 2019.

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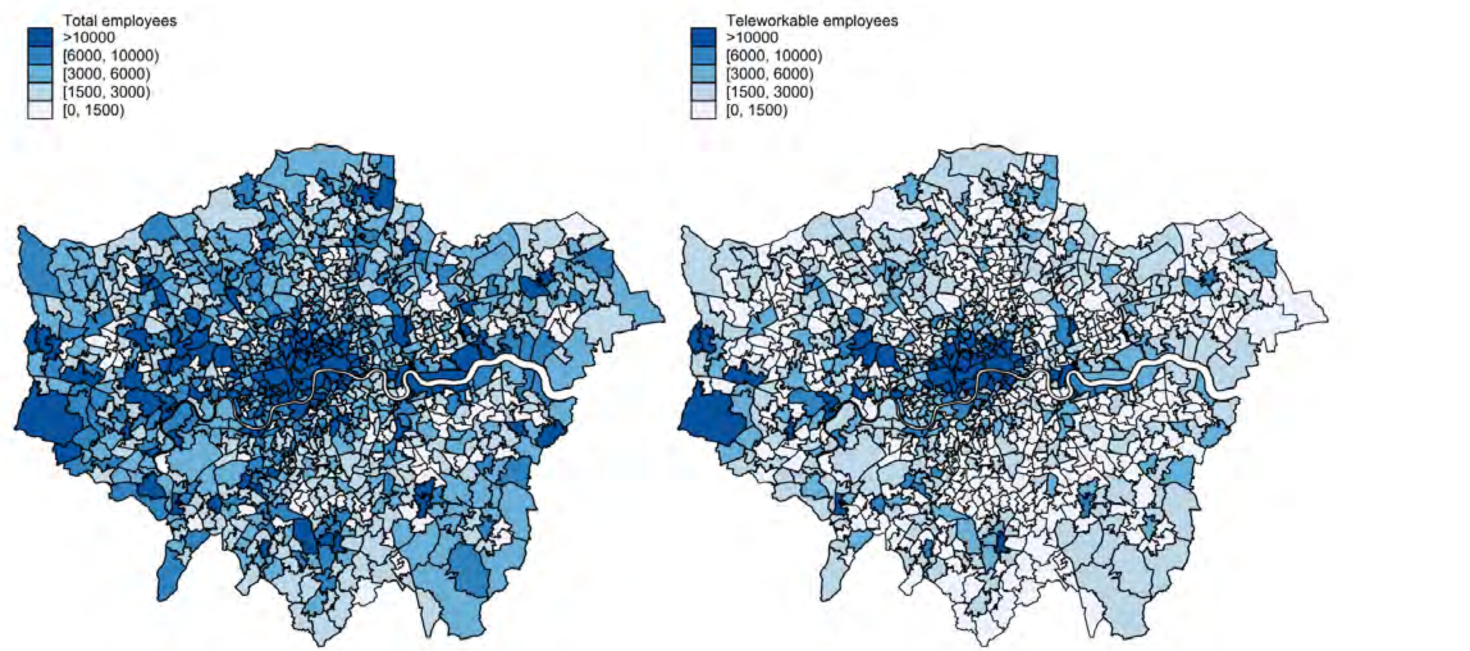
Figure 4:
Employees and employment suitable for working-from-home, Greater London Authority



Note: The maps show the netflow of workers from each area (see the note to Figure 3 for details). On the LHS, each area is an MSOA, on the RHS a London Borough.
Data source: ONS Business Structure Database , 2018. Proportion of homework by MSOA based on authors calculations using information from the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019.

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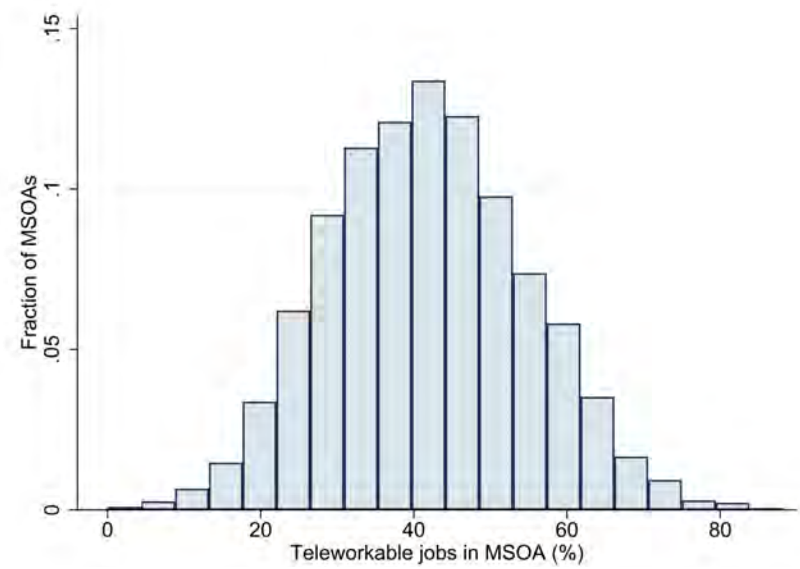
Figure 5:
Geographical differences in suitably of jobs for working-from-home.



Note: The horizontal axis reports the estimated percent of total employment, within an MSOA, that is suitable for working-from-home.
Data source: Authors' calculation based on data from the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019.

Both maps show that neighbouring areas may have widely varying proportion of workers with the ability to work remotely. This is summarised more generally for the whole of the UK in Figure 5. In some MSOAs more than 60% of residents can work-from-home, while in many others only fewer than 30% of residents can work-from-home. The same is true at local authority level. As we shall see, it is this heterogeneity that gives the Zoomshock its bite. In Figure (6) we illustrate the Zoomshock for the Greater London Authority, at the level of the MSOA (ζ_z from Equation (2)) and aggregated to the local author-

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ity ($\widehat{\zeta}_A$ from Equation (4)). Both maps confirm the familiar pattern of workers living on the periphery of the metropolis and working in the inner city. If MSOA Zoomshocks are generated within local authorities, we would expect to see $\widehat{\zeta}_A \approx 0$. These maps demonstrate that this is not the case, workers in central London are commuting from beyond the local authority.[6]

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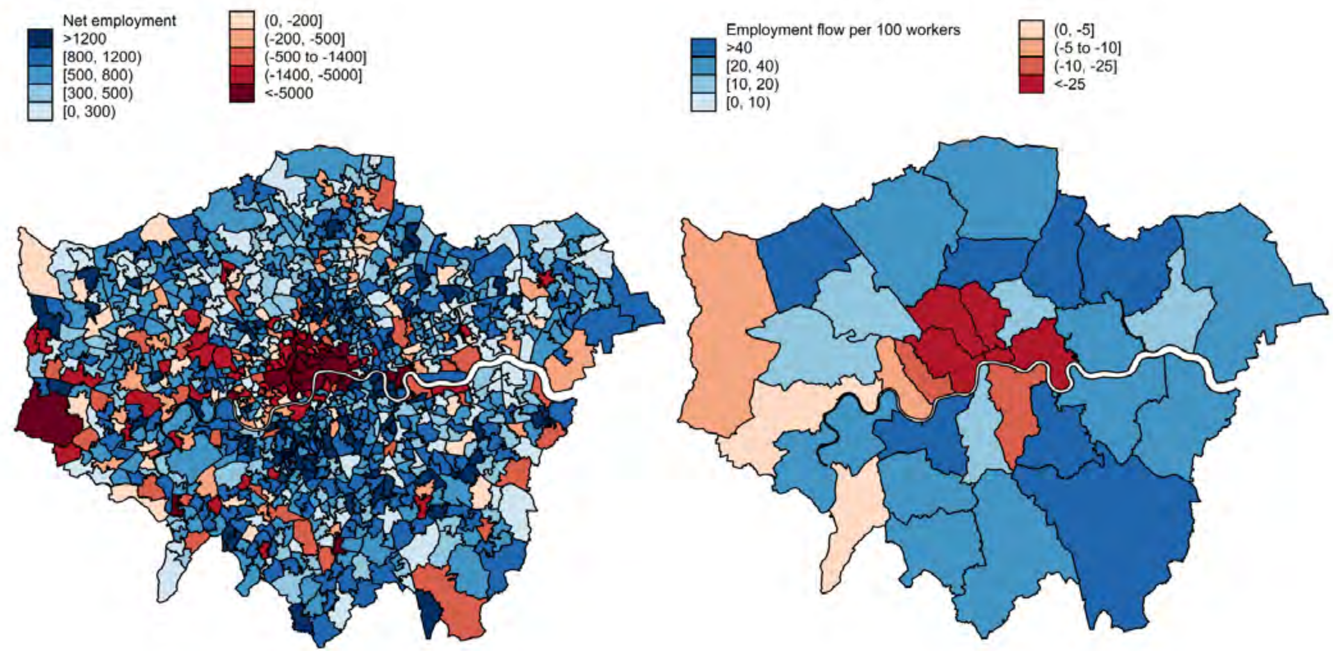
[6]The deep-red colouring of some areas on the western border of London also reflects this.

Figure 6:
Zoomshock, Greater London Authority



Note: These maps show quantiles of expressions (2) and (3) by MSOA (left) and local authority (right). Quantile boundaries are calculated separately for positive and negative shocks to represent the 25th, 50th, 75th, and 95th percentiles for Great Britain in the left-hand side map and the 25th, 50th, 75th, and 95th percentiles for Great Britain in the right-hand side map.
Data source: Authors' calculation based on data from the ONS *Annual Survey of Hours and Earnings*, 2017, 2018, 2019.

These maps illustrate the importance of a very granular view: there are sharp, often extreme, differences among neighbouring areas. These differences are lost when a coarse partition is chosen. The map on the LHS in Figure 6 shows a more fragmented distribution, indicating that there are substantial variations within boroughs. This can be seen in more detail in the close up of the London boroughs of Hackney and Kensington and Chelsea that we show in Figures 7a and 7b. Even though Hackney as a whole is an area of net inflow (more people are returning than are leaving), there are pockets with a large net outflow (those in pink and deep red in the map). The picture is similar, if with the reverse signs, for Kensington and Chelsea; patterns of deep red neighbour areas of blue.

This is not just a London (or Bassetlaw) phenomenon. We also report the Zoomshocks for (the nine local authorities of) Greater Birmingham and Solihull, for (the ten local authorities in) Greater Manchester, and for (the four local authorities in) the Sheffield City Region: these are Figures 8-10. Again these highlight the highly asymmetric pattern of commuting from where people live to where people work: some areas predominantly serve as residences, others are mainly places for work. In the Appendix to this paper (`https://perma.cc/P6RR-NMW4`), we provide Zoomshock maps for a wide variety of LADs and counties across England, Wales and Scotland.

In Figure 11, we map $\widehat{\zeta}_A$ by local authorities for the the whole of Great Britain (omitting the Shetland and Orkney Islands). A couple of interesting features are worth point out. First, the majority of the areas on the map are blue, suggesting a positive Zoomshock. This is unsurprising, as pre-home-working economic activity tends to concentrate in few, relatively dense, geographic areas. Second,

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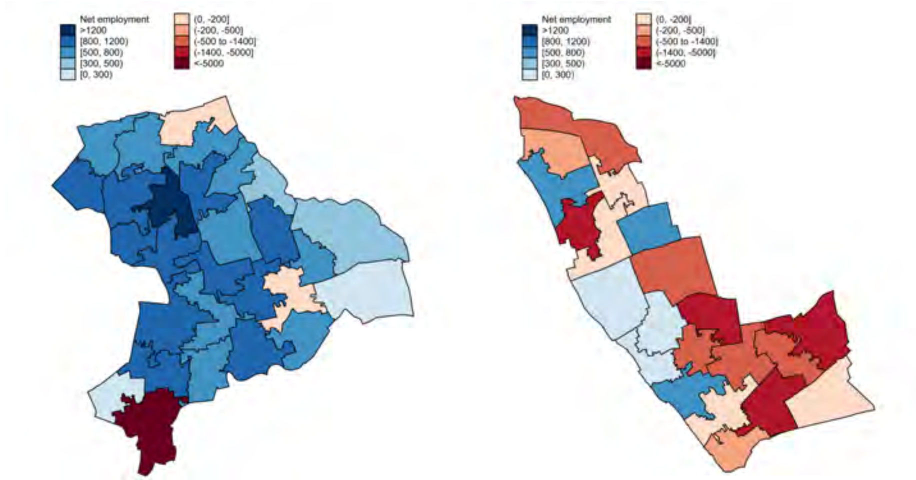
Figure 7:
Zoomshock, Hackney and Kensington & Chelsea

(a) Hackney (b) Kensington and Chelsea



Note: This map shows quantiles of Expression (2) by local authority. Quantiles boundaries represent the 25th, 50th, 75th, and 95th percentiles for Great Britain, calculated separately for positive and negative shocks.
Data source: Authors' calculation based on data from the ONS *Annual Survey of Hours and Earnings*, 2017, 2018, 2019.

larger (in terms of area) local authorities appear to be more likely to have positive Zoomshocks, while small local authorities are more likely to have negative Zoomshocks. This reflects an important feature of the Zoomshock, economic activity is flowing to less-densely populated parts of Britain. These features both suggest that working-from-home is leading to economic activity being significantly less geographically concentrated.

In Table 1 we list the ten local authorities with the largest negative and positive Zoomshocks. The top of the list of negative shocks is perhaps somewhat

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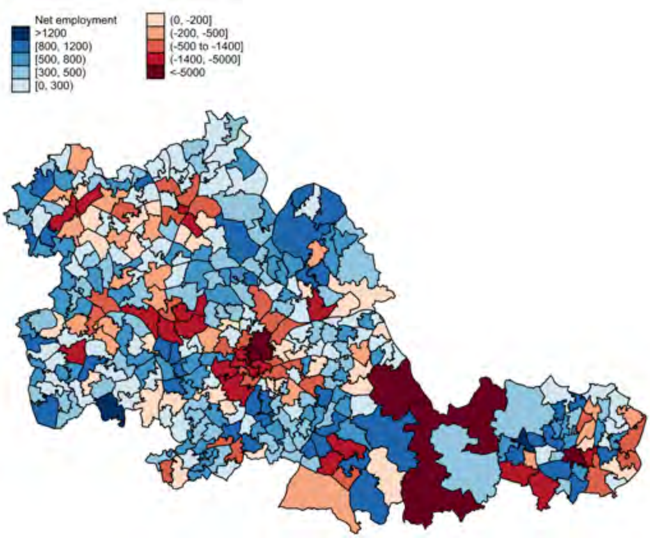
Figure 8:
Zoomshock, Greater Birmingham and Solihul



Note: This map shows quantiles of Expression (2) by local authority. Quantiles boundaries represent the 25th, 50th, 75th, and 95th percentiles for Great Britain, calculated separately for positive and negative shocks.
Data source: Authors' calculation based on data from the ONS *Annual Survey of Hours and Earnings*, 2017, 2018, 2019.

predictable, as six of the top ten are in Central London. However, other local authorities, such as Nottingham and Newcastle are perhaps a little more surprising. The magnitude of the Zoomshocks are substantial—three-quarters of workers in the City of London and half of those in Westminster can work-from-home. The boroughs with the largest positive shocks are again predominantly in London, although now they reflect the primarily residential authorities of outer London.

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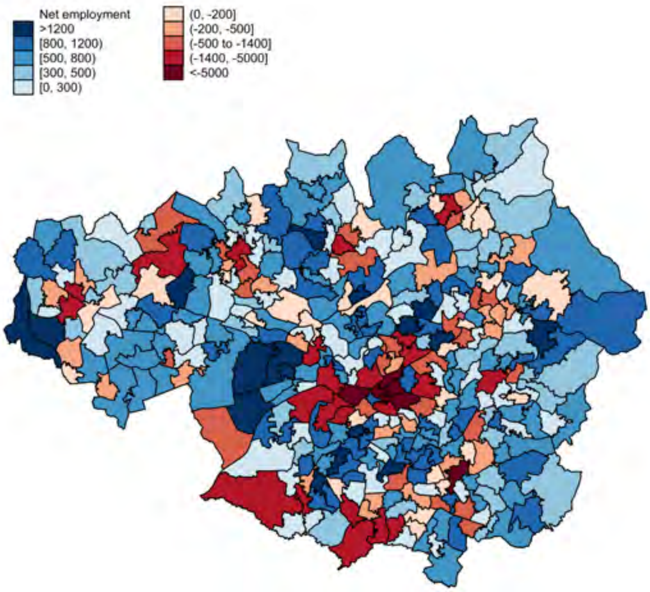
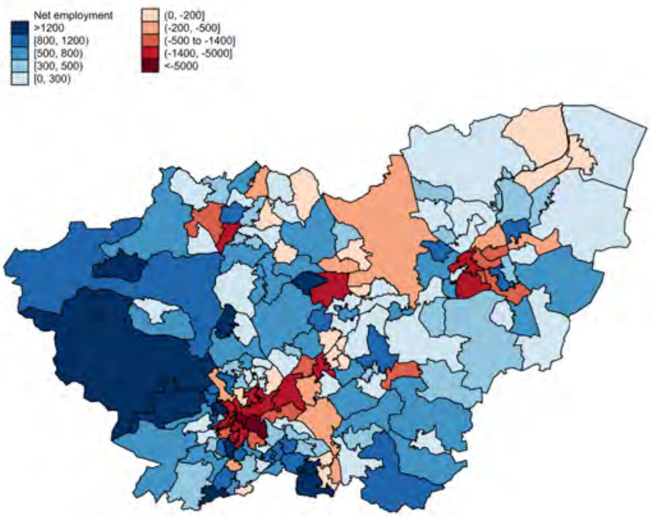
Figure 9:
Zoomshock, Greater Manchester



Note: This map shows quantiles of Expression (2) by local authority. Quantiles boundaries represent the 25th, 50th, 75th, and 95th percentiles for Great Britain, calculated separately for positive and negative shocks.
Data source: Authors' calculation based on data from the ONS *Annual Survey of Hours and Earnings*, 2017, 2018, 2019.

Another interesting feature of the data is the differences in the GDP shock. East Dunbartonshire has a larger increase in the number of workers than East Renfrewshire, but the implied increase in GDP is only around one third of the size. This emphasises that not only is there important heterogeneity in the numbers of workers in an MSOA able to work-from-home but there is also substantial variation in how much they earn and likely spend. This is important as it suggests that there may be a reversal of fortune, the most prosperous areas, like

Figure 10:
Zoomshock, Sheffield City Region



Note: This map shows quantiles of Expression (2) by local authority. Quantiles boundaries represent the 25th, 50th, 75th, and 95th percentiles for Great Britain, calculated separately for positive and negative shocks.
Data source: Authors' calculation based on data from the ONS *Annual Survey of Hours and Earnings*, 2017, 2018, 2019.

the City of London, previously characterised by large numbers of highly paid commuters are the places most affected. One thing this highlights is that the places that might be most affected are those where, even if fewer in number, commuters account for a large share of GDP.

5 The Zoomshock and LCS workers

The analysis so far illustrates the considerable variability of the Zoomshock across MSOAs. In this section we analyse the implications of this variation for

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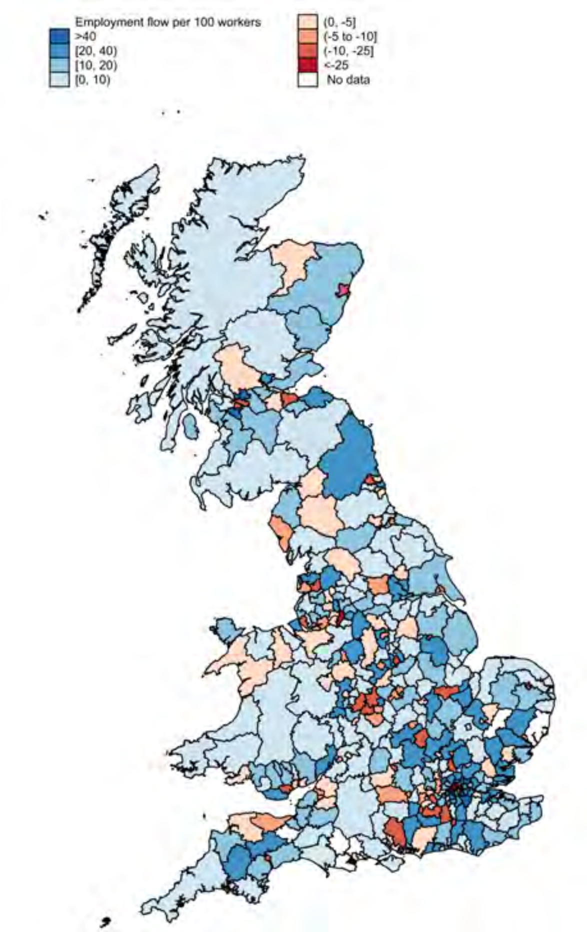
Figure 11:
Zoomshock, Great Britain local authorities



Note: The maps show the netflow of workers from each MSOA (Equation (2), see the note to Figure 3 for details).
Data source: Authors' calculation based on data from the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019.

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Table 1:
Largest negative and positive Zoomshock by local authority

Local authority	$\widehat{\zeta}_A$ (workers)	$\widehat{\zeta}^y_A$ (GDP†)
Negative		
City of London	-75.6	-2,592,970
Westminster	-49.9	-1,218,470
Camden	-43.1	-648,598
Tower Hamlets	-33.9	-1,234,626
Islington	-30.4	-587,529
Manchester	-25.1	-410,680
Southwark	-24.4	-470,561
Cambridge	-23.3	-371,215
Newcastle upon Tyne	-22.2	-267,416
Nottingham	-21.5	-277,061
Positive		
Redbridge	69.1	1,341,043
Lewisham	64.6	1,294,023
Harrow	61.9	1,200,129
Waltham Forest	60.3	1,156,035
East Dunbartonshire	57.4	384,360
East Renfrewshire	52.8	1,050,853
Haringey	46.8	936,223
Gosport	42.3	613,793
Wandsworth	41.3	1,474,134
Bromley	40.7	1,087,333

Calculations correspond to expressions (4) and (6).
†GDP shown as pounds per annum.
Data source: Authors' calculation based on data from the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019.

the LCS sector. The key point is that while the Zoomshock is itself additive across zones—as can be seen from expressions (3) and (5)—the consequences of the Zoomshock for area employment in the LCS industry are almost certainly

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not additive. This is because the presence of frictions, such as imperfect labour mobility and capacity constraints, means that a movement in LCS demand from one zone to another will not, in the short- and medium-run, be perfectly mirrored by a movement in LCS supply.[7] As a result, we expect to see a decrease in aggregate LCS employment, with wages increasing in positive Zoomshock neighbourhoods.

A complete formal analysis is beyond the scope of this paper, instead in this section we present an intuitive graphical analysis of the short-medium run effects of the Zoomshock on the distribution of LCS employment and economic activity. We show that the aggregate impact on LCS employment in a LAD depends crucially on the shape of the distribution, and specifically the skewness of positive MSOA Zoomshocks.

To this end, Figure 12 depicts the demand and the supply for LCS workers in zone z in the pre-Zoomshock equilibrium, given by (L_z^*, w_z^*), where L_z is the number of LCS workers and w_z is the wage. To simplify the analysis we make the assumption that all the demand for LCS workers comes from non-LCS workers. This strong assumption is only to aid calculations and carve in sharper relief the distinction between the two groups of workers.[8] The pre-Zoomshock intersection of demand and supply in zone z reflects a long-run spatial equilibrium. This is reflected by the shape of the supply function, depicted as the dashed curve where LCS workers are in their preferred job and residence. From

[7] To focus on the effect of the geographic change in *where* work is done, we assume that LCS demand from workers is independent of whether they work from home or the office. This is likely an overly-optimistic assumption. For example, having access to a one's own kitchen may decrease demand for restaurant food when one works at home relative to the office.

[8] Thus, a barber (who is a LCS worker) may have lunch in a local restaurant, and if he stops working, due to the fact that many of his customers are teleworking, the restaurant will lose the barber's custom as well, amplifying the effect of the non-LCS worker remote working.

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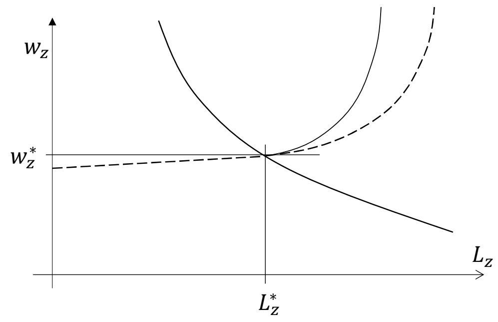
Figure 12:
Equilibrium in the LCS labour market in zone z.



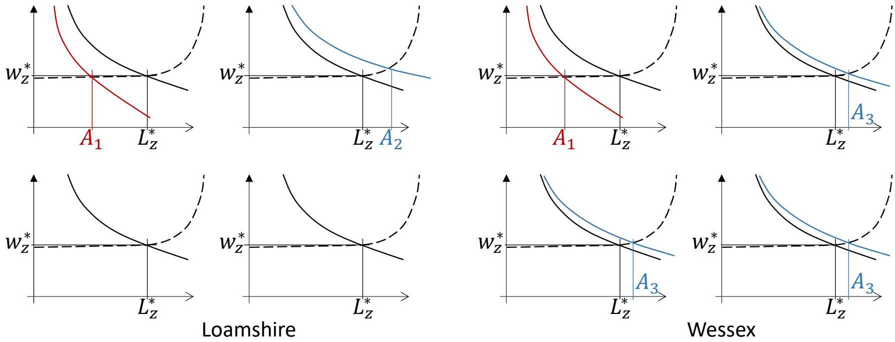
Note: This figure illustrates the market for LCS workers in a zone z. The downward sloping curve shows demand for workers (L_z) at each wage (w_z). The dashed and solid upward sloping curves depict two possible supply curves for z.

this equilibrium in order to attract new LCS workers, businesses in zone z will need to pay progressively higher salaries. Initially, the increase might only need to be small to attract workers close to indifferent between their current zone and zone z, but then larger increases will be needed to persuade others to move to or to commute to zone z. The shape of the supply function, in particular the "steepness" of the curve beyond the initial equilibrium, depends on the characteristics of zone z, such as the geographical proximity and type of neighbouring zones. As an example, in a sparsely populated zone an LCS business may find that larger wage increases are necessary to attract additional staff, who would have to travel substantial distances to work.[9]

The aggregate effect of the Zoomshock on LCS employment for a LAD depends on the distribution of the shock across the MSOAs that make up the LAD.

[9]The steepness of the curve will depend on the willingness of unemployed LCS workers to commute as well as on capacity-constraints, etc. Marinescu and Rathelot (2018) show that in the US job-seekers are a around third less likely to apply to a job 10 miles away.

Figure 13:
The equilibrium in zone z prior to the Zoomshock. Right skewness.



Note: This figure illustrates possible Zoomshocks for eight zones across two fictional areas.

In Figure 13 we illustrate this for two fictional LADs, Loamshire and Wessex, each containing four MSOAs, one in each quadrant of the LAD. To highlight the aspects that affect the link between the overall effect of the Zoomshock and the shape of the distribution of these shocks in the area, we make assumptions which are deliberately extreme. The demand function for LCS (black solid curve) is identical in all eight areas, and so in the long run equilibrium each area has the same employment for LCS workers who are all paid the same wage. The eight demand and supply diagrams in Figure 13 depict the LCS market in each of these MSOAs.

We also posit the supply functions to be the same in the eight zones. This again is to highlight the role of skewness in the Zoomshock, and could be relaxed with no change in the results. What matters is that, beyond the pre-shock equilibrium the supply is convex; as we argue above, this is plausible. Figure 13

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depicts a large decrease in demand (brought on by a negative Zoomshock) in the north-east MSOA of each of Loamshire and Wessex. In these zones, half the workers stop commuting there to work and instead work-from-home. This is represented by the demand function for LCS workers in these areas shifting to the red curve, where LCS labour demand at the previous salary, is exactly half as it was before. What distinguishes Loamshire and Wessex is where the teleworkers reside. In Loamshire they all live in the north-easterly MSOAs. In this MSOA the demand curve shifts to that of the blue line: the demand has increased by 50%, a rightward shift equal in size to the leftward shift of the red curve in the north-west. In the two other MSOA there is no change, as no one previously commuted to or from them, so the equilibrium in these two "southern" MSOAs is unaltered. The total employment of LCS workers in Loamshire changes by the difference between the the decrease in the north-west zone, the distance between L_z^* and A_1, and the increase in the north-east zone, the distance between A_2 and L_z^*. That, is, the total employment in Loamshire following the Zoomshock is $2L_z^* + A_1 + A_2$.

But now consider Wessex: here the workers who were commuting to the north-west zone and are now teleworking are evenly distributed across the rest of the LAD, so that in each of the three other MSOAs, the demand curve for LCS workers shifts by a third of the distance of the shift in the north-east MSOA in Loamshire, as depicted in the RHS panel of Figure 13. The analogous argument shows that the post-Zoomshock employment in Wessex is $A_1 + 3A_3$. The convexity of the supply of labour beyond the pre-Zoomshock equilibrium implies that the distance between A_2 and L_z^* is less than three times the distance between A_3 and L_z^*. This implies that the total loss of employment due to the

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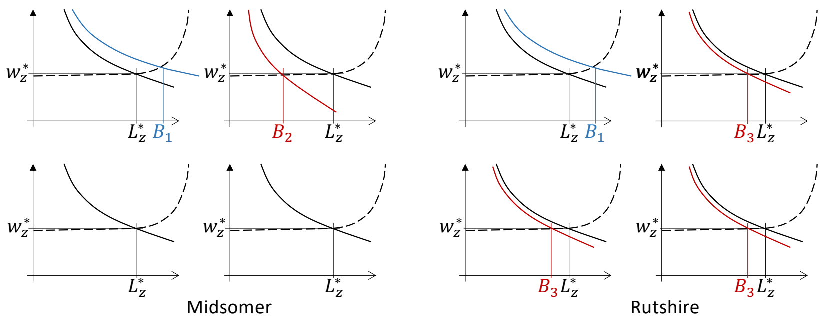
Figure 14:
The equilibrium in zone z prior to the Zoomshock. Left skewness.



Note: This figure illustrates possible Zoomshocks for eight zones across two fictional areas.

fact that workers cannot relocate frictionlessly between MSOAs is greater in Loamshire. Thus in the comparison between the two counties, the loss of LCS employment depends not on the magnitude of the aggregate Zoomshock, but on the skewness of the distribution of the shocks: Wessex's distribution is more skewed than Loamshire's (which is in fact symmetric).

The next figure shows however that it is only right skweness (that is positive skewness) that matters. In Midsomer, the shock pattern is symmetric, exactly the same as in Loamshire, whereas the county of Rutshire, has one MSOA with the same positive shock as Midsomer, the north-west in both counties, but smaller negative shocks in the three other MSOA, making the shock distribution in the county left skewed. Yet the overall impact on LCS employment is the same in Rutshire and in Midsomer, due to the linearity of the supply function to the left of the pre-shock equilibrium.

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There are already two lessons to take from this preliminary analysis. The first is that, in aggregate, we expect the Zoomshock will lead to a decrease in LCS employment. This is a consequence of short-run labour market frictions and capital availability that mean a shift in LCS demand from one neighbourhood to another will not be mirrored by a similar shift supply. The second lesson is that we expect the consequences for employment across an LAD to be worse the more skewed is the Zoomshock across the MSOAs which make up the LAD.

5.1 The Zoomshock and Locally Consumed Services: Some Evidence

There is significant anecdotal evidence of the negative impact that the Covid-19 pandemic has had on the LCS industry, particularly in urban centres such as central London. Given the large negative Zoomshock we estimate for central London (Figure 6), this is not surprising. We now provide quantitative evidence as to the scale and distribution of this shock. As stated in the introduction, we define LCS as any good or service for which the market is geographically constrained, both supply and demand must take place in a fixed geographic location. Restaurants, hairdresser and theatres are obvious examples. Although the goods purchased in a department store are not part of locally consumed services *per se*, the service provided by the department store, providing an outlet and assistance in which to purchase goods, is a local service.[10] We define businesses and employees in the locally consumed service industry according to 615

[10] Our definition of local services is closely related to the *tradeable* and *non-tradeable* goods nomenclature, as in Mian and Sufi (2014).

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four-digit Standardized Industry Classification codes.

The overall distribution is shown in Figure 15. Here we see that, both within the Greater London Area (left panel) and outside it (right panel), the proportion of MSOAs experiencing a negative shock is increasing with the number of the local service employees. That is, in our data, LCS employment is concentrated in neighbourhoods in which there are many jobs suitable for working-from-home. The average MSOA which experiences a positive Zoomshock has 687 employees working (pre-Covid-19) in LCS within the MSOA. The average MSOA experiencing a negative Zoomshock has 2139 employees working (pre-Covid-19) in LCS within the MSOA. Despite the fact that only 28% of MSOAs are predicted to experience a negative Zoomshock (1990 MSOAs), these MSOAs account for 54% of all the local service employment. Overall, in Britain 4,252,963 employees suffer a negative shock, against versus 3,583,376 employees in MSOAs experiencing a positive shock.

Figure 15 shows that a small number of MSOAs are experiencing very large Zoomshocks, an increase in employment in some cases of over 300%. These large changes are concentrated in the MSOAs with the fewest LCS employees. For most MSOAs experiencing a positive shock this is smaller, reflected by the mass of points just above the red-dashed horizontal line which separates positive and negative shocks. This combination implies the distribution of positive shocks to be characterised by most shocks being small and close to the mode, with a few large shocks far to the right. That is, right-skewed. Moreover, the largest shocks have been in MSOAs where the composition of employment suggests there is the least existing capacity. It is reasonable to suspect that this limited capacity will mean that there will be less ability to absorb these increases.

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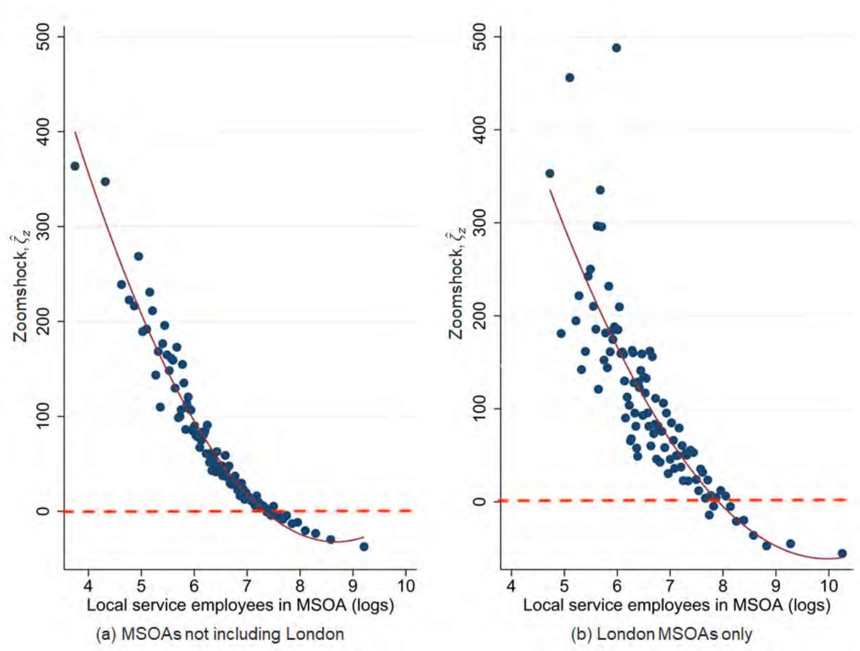
Recall from Figure 14, that while the data also show that distribution of negative shocks is also skewed—this is not what matters for the aggregate outcome. While, the right-most observations in the left and right panels represent an average of over 8,000 and 22,000 employees respectively it isn't the concentration of these losses, but rather the inability of MSOAs experiencing positive shocks to re-employ them that leads to the negative aggregate effect on LCS employment.

This is the UK government's official measure of relative deprivation. It is based on 39 separate indicators and aims to capture the lack of resources needed to meet needs across a wide range of an individual's living conditions, not just lack of financial resources.

We close our analysis by noting that the losses in LCS employment are likely to exacerbate geographic inequality. Figure 16 shows that LCS workers are disproportionately likely to live in MSOAs high Index of Multiple Deprivation scores.[11] In the most deprived MSOAs, roughly 45% of residents are employed in the LCS sector. Thus, the skewness of the negative shock distribution may not matter for the overall level of LCS employment losses, but to the extent that workers in MSOAs with the most negative shocks live in similar locations, we may expect the increase in poverty to be highly geographically concentrated. This concentration might have important policy implications.

[11] This is the UK government's official measure of relative deprivation. It is based on 39 separate indicators and aims to capture the lack of resources needed to meet needs across a wide range of an individual's living conditions, not just lack of financial resources.

Figure 15:
Zoomshock and local service employment



Note: This figure regresses, for each MSOA, the Zoomshock (Equation 4) against the log-employment in the local service industry. Binned into 100 evenly sized groups.
Data source: Change in MSOA employment based on authors' calculation using the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019. Log-employment in local services by MSOA calculated using information from the ONS Business Structure Database, 2018.

6 Conclusion

This paper looks at an important economic consequence of the Covid-19 pandemic. The pandemic has lead to a significant shift in the geographic distribution of economic activity as workers who can work from home, do so. We refer

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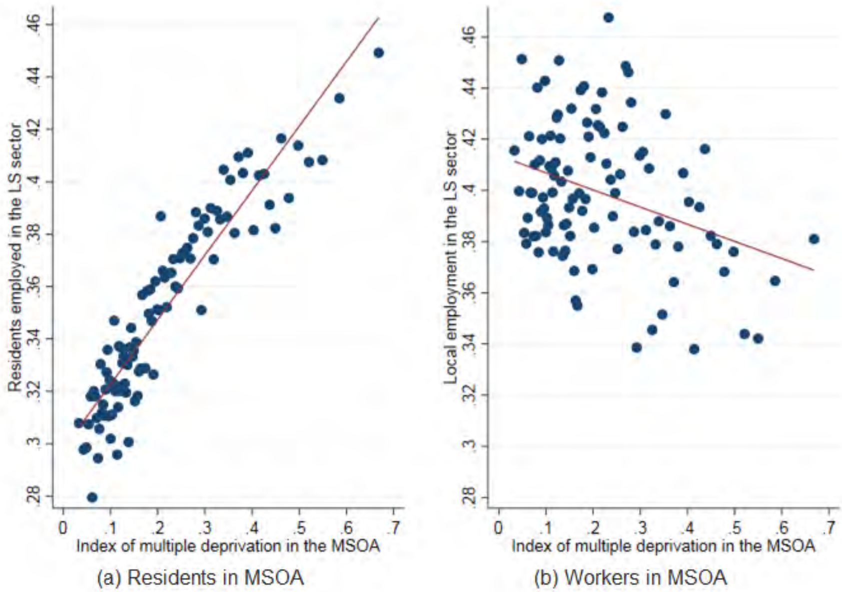
Figure 16:
Index of Multiple Deprivation



Note: Binscatter plot: each of the dots represents many MSOAs, to avoid cluttering the diagram.
Data source: Percent employment in local services by MSOA calculated using information from the ONS Business Structure Database, 2018.

to this redistribution as the Zoomshock.

There are three takeaways from our results. First, the Zoomshock is large—many people can work form home and many people live in a different neighbourhood from the one where they work. This is true both for specific neighbourhoods and when we aggregate to the level of local authorities. Second, the Zoomshock is extremely heterogeneous. Within UK local authorities, some neighbourhoods have experienced a very large decline in economic activity

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while others have seen a surge. In general, while the most prominent feature of the Zoomshock has been the relocation of economic activity from a few densely populated city centres to the suburbs, the precise changes are often quite different in seemingly similar neighbourhoods. Third, the Zoomshock is moving workers away from neighbourhoods with a large supply of locally consumed services to neighbourhoods where the supply of these services is relatively scarce. As LCS are, by definition, geographically immobile in the short-run, this suggests a possible geographic mismatch of supply and demand that may have consequences for aggregate LCS employment. We found that the scale of the losses depends crucially on the shape of the distribution of Zoomshocks, and in particular that what matters is the skewness of positive shocks. If the positive shocks are approximately uniformly distributed, then losses due to frictions, such as capacity constraints, will be lower than if the Zoomshock is concentrated on a small number of neighbourhoods. This makes it crucial to obtain a precise measure of the Zoomshock at a highly granular level.

An objective of this exercise is to produce guidance for policy makers in the UK, and in other countries, in the formulation of a Covid-19 economic recovery strategy. The exact nature of the policy prescription depends on how long-lived will be the increase in working-from-home. If we expect that once the UK emerges from the current public health crisis, workers will return to the office and pre-Covid-19 economic activities are restored, then there is a role for policy to aid local service businesses that are currently struggling to survive. In this case aid should focus in neighbourhoods which are experiencing the largest negative Zoomshocks. If, on the other hand, we expect a significant fraction of work to continue to take place at home once public health restrictions are eased, then policy should encourage and facilitate LCS businesses relocating to where is the demand. That is, businesses in LCS industries should be encouraged to move from neighbourhoods experiencing large negative Zoomshocks to neighbourhoods with positive Zoomshocks. Further understanding of the impact of the Zoomshock on economic activity will also be needed in view of the fact that the different characteristics of the zones experiencing positive and negative Zoomshocks will affect their ability to support LCS businesses: for example a large café thriving in a busy city centre may not survive in a well-to-do sparsely populated rural environment.

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Policies to support businesses through the COVID-19 shock: A firm-level perspective[1]

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Relying on a novel dataset covering more than 120,000 firms in 60 countries, this paper contributes to the debate about policies to support businesses through the COVID-19 pandemic. While governments around the world have implemented a wide range of policy support measures, evidence on the reach of these policies, the alignment of measures with firm needs, and their targeting and effectiveness remains scarce. This paper provides the most comprehensive assessment to date of these issues, focusing primarily on the developing economies. It shows that policy reach has been limited, especially for the more vulnerable firms and countries, and identifies mismatches between policies provided and policies most sought. It also provides some indicative evidence regarding mistargeting of policies and their effectiveness in addressing liquidity constraints and preventing layoffs. This assessment provides some early guidance to policymakers on tailoring their COVID-19 business support packages and points to new directions in data and research efforts needed to guide policy responses to the current pandemic and future crises.

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1. Introduction

The economic impact of the COVID-19 pandemic has been severe and persistent. In 2020, the global economy is expected to experience its worst recession since the great depression of the 1930s with the highest share of countries experiencing contractions in per capita GDP since 1870 (WBG, 2020).[1] Estimates by Apedo-Amah et al. (2020) show that firm sales declined by more than 70% around the peak of the crisis (as measured by the steepest drop in Google Mobility), and have remained more than 40% below last year's levels even several months later. Two-thirds of firms have either fired employees, reduced worker hours or wages, or asked workers to take leave. More than half of micro and small businesses (those with less than 20 employees) are in arrears or expect to fall into arrears in the next six months. And while there are welcome news of vaccines and new treatments for COVID-19, these are unlikely to be available everywhere at once meaning that the economic pain is likely to persist for some time.

In response to the crisis, governments around the world have relied on a wide range of policy measures to support firms and households. While these responses have been uneven across countries, they are unprecedented in their magnitude. Fiscal stimulus in high-income economies has reached 10% of GDP or more, with around 40% going to firm support. In developing countries, faced with more limited fiscal space, governments have allocated between 1% and 3% of GDP to this purpose, with about a quarter of this amount dedicated to supporting businesses. Irrespective of the amount of the resources invested, data on whether these are reaching the intended beneficiaries, addressing their needs, and helping firms adjust to COVID-19 are desperately needed to inform policy-making. This paper provides the first such assessment on a global scale.

Specifically, the paper utilizes a unique dataset covering more than 120,000 firms across 60 countries during the months of April-September 2020 to present a set of novel stylized facts on the policies implemented to support businesses from a firm-level perspective. It characterizes the beneficiaries of implemented policies, contrasts the policies implemented with ones that firms state are most important to them, identifies reasons for not accessing policy support, and links policies with firm performance, layoffs, expectations, and uncertainty. The paper also provides some initial indicative evidence about the targeting and effectiveness of policies.

Our main findings are grouped into four sets of stylized facts. First, we show that policy support has been especially limited for the most vulnerable firms and countries: micro firms are about half as likely to access support as large firms, and firms in high-income countries are about five times more likely to receive public support than firms in low-incomes countries. Second, we identify some mismatches between policies reported as most needed by firms and policies that firms are more likely to receive, particularly in upper-middle and high-income countries. Third, we document that targeting of initial policy responses was limited as well as some *mistargeting*, likely as a result of barriers to access support and lack of targeting capacity, with firms that did not experience shock or sales drop benefiting from support and firms experiencing large negative shocks not having access to public support. Fourth, we find indicative evidence of effectiveness: our results show that policies such as credit and cash transfers appear to be helping firms address liquidity constraints while receiving wage subsidies seems to be associated with lower probability of firing workers.

[1]The World Bank forecasts that the global economy will contract by 5.2 percent in 2020 (WBG, 2020).

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This paper contributes to several related strands of the literature. Recently published volumes such as Baldwin and di Mauro (2020) have reviewed the range of emerging policy responses to COVID-19 and provided advice on how policy frameworks should evolve – although most of the focus has been on high-income economies and China. Authors such as Cororaton and Rosen (2020), Granja et al. (2020), De Marco (2020), Kozeniauskas et al. (2020), and Cui et al. (2020) have focused on the reach and targeting of specific programs in China, Italy, Portugal, and the US. Additionally, this paper contributes to the emerging literature by authors including Chetty et al. (2020), Granja et al. (2020), **?**, and Cui et al. (2020) that have provided some early evidence on the effectiveness of programs to help firms weather the impacts of the pandemic in the same countries, as well as previous studies such as De Mel et al. (2012) and Bruhn (2020) that focused on experimental and quasi-experimental evidence from previous crises in Sri Lanka and Mexico.

The rest of the paper is structured as follows. The next section presents the data. The following two sections present policies that have been announced, including evidence on access to policies, as well as policies that firms identify as more needed. Then, we present evidence on mismatches between the demand and supply of policies, mistargeting, and barriers to accessing public support. Recognizing that the COVID-19 crisis has significantly altered firms outlook and heightened uncertainty (Altig et al., 2020), the section that follows specifically focuses on the relationship between receiving policy support and firms expectations and uncertainty. Lastly, we present some preliminary evidence about the effectiveness of different policies. The paper concludes with a discussion of policy implications and directions for future research.

2. Data

We rely on data from the first wave of the Business Pulse Surveys (BPS) developed by the World Bank Group (WBG) to measure the impact of the COVID-19 pandemic on the private sector (Apedo-Amah et al., 2020), as well as the COVID-19 follow-up rounds of the World Bank Enterprise Surveys. This novel harmonized dataset offers the most comprehensive assessment of the short-term impact of the shock (from April through August of 2020). The sample includes more than 120,000 businesses in 60 low, middle, and high-income countries in the six regions where the WBG is present.[2] The sample covers micro, small, medium, and large businesses across all main sectors (agriculture, manufacturing, retail, and other services, including construction).

The questionnaire collects information on business performance through the COVID-19 shock on some critical economic dimensions: operations of the business, sales, liquidity and insolvency, labor adjustments, firms responses, and expectations and uncertainty about the future (Apedo-Amah et al., 2020). Businesses are asked about their preferred mechanisms of support during the pandemic. We grouped these mechanisms in the following categories of policy instruments: monetary transfers, deferral of payments, access to finance, support with tax obligations, wage subsidies, and others.[3] Businesses are also surveyed on whether they have received any of these mechanisms of support

[2]The survey covers East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), Middle East and North-Africa (MNA), South Asia (SAR), and Sub-Saharan Africa (SSA). Among high-income countries, our dataset includes Cyprus, Greece, Italy, Poland, Romania, and Slovenia.

[3]The menu of policies differed in some countries, but in most cases options can be harmonized in these categories.

from local or national authorities, and if they have not, they are asked about the reasons why.[4] The dataset then offers a unique window into the private sector to assess both the need for policy and the availability of public support during the COVID-19 shock.

Given the variation in country samples and timing of the surveys, we follow Apedo-Amah et al. (2020) and introduce different controls in the analysis. Unless stated otherwise, we usually include in the analysis dummies for size, sector (i.e. 10 sectors), country, and the timing of the survey in terms of weeks relative to the peak of the COVID-19 shock.[5] To control for differences in the number of observations in each country sample, we weight our results using the inverse of the number of observations in each country, that is, in the spirit of traditional cross-country analysis, each country has the same weight in our analysis.

3. The supply and access to policy support

To respond to the economic downturn caused by the COVID-19 pandemic, countries around the world have enacted a large suite of stabilization and recovery measures. According to the World Bank, governments across the world have implemented 1,607 measures directly aimed at supporting firms in 135 countries. More than three quarters of these measures are concentrated in three categories: debt finance support, employment cost support, and tax support.[6] Debt finance support has been the most common, accounting for more than a third of all policy measures adopted. Within this category, new lending under concessional terms accounts for 43%, followed by the deferral, restructuring or rescheduling of payments (26%) and credit guarantees (13%). Employment support constitutes roughly one quarter of all measures that have been announced, with wage subsidies (38%) and support to self-employed individuals (26%) being the most common within this group. The third most common group of policy response measures is tax relief, representing one-fifth of all measures.[7]

Importantly, the type of policy responses varies systematically across countries. Low income countries tend to use a less-diversified set of interventions, with debt finance interventions accounting for almost half of all measures, but rely less heavily on employment support. High-income countries rely less heavily on debt finance or tax relief (31% and 17% of all measures, respectively), but use employment support measures (32%) more frequently. More direct forms of income transfers, i.e. wage subsidies and direct monetary transfers, are more common among firms in richer countries. Such differences suggest that variations in government administrative capabilities, fiscal space, the

[4]The questions read: *1. What would be the most needed policies to support this business over the COVID-19 crisis?* (*Choose up to three*) Menu of options: monetary transfers, deferral of payments, access to finance, support with tax obligations, wage subsidies, and others; *2. Since the outbreak of COVID-19, has this establishment received any national or local government measures issued in response to the crisis?* Menu of options: Yes, No; *3. Did any of these measures involve any of the following?* (*Choose all that apply*) Menu of options: monetary transfers, deferral of payments, access to finance, support with tax obligations, wage subsidies, and others; *4. What of the following options best describe the reason why this establishment did not receive any national or local government measures issued in response to the crisis?* Menu of options: I was not aware; Too difficult to apply; I am not eligible; I have applied but not received it; Other.

[5]This is measured using country-level Google Mobility Data.

[6]See World Bank, *Map of SME-Support Measures in Response to COVID-19*. Data and visualizations available here: https://bit.ly/2SelF96. Policy responses are classified in eight different categories: business advice; business climate; business cost support; debt finance support; demand support measures; employment cost support; other finance support; and tax relief.

[7]Primarily through rate reductions, credits, waivers, and/or deferrals of VAT, payroll, social security, and land taxes (58% of all tax support measures); similar benefits on corporate taxes have been used to a lesser degree (30%).

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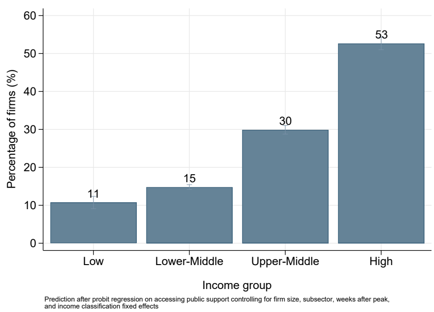
extent of informality, financial sector development and the reach of the tax system, determine the policy toolkit available to governments in each country.[8]

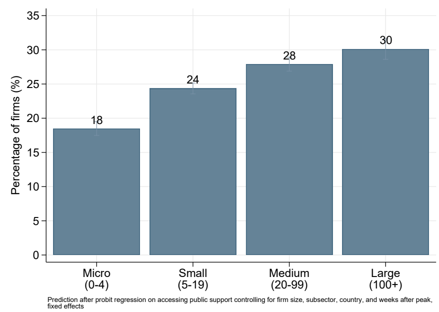
Despite the plethora of measures launched around the globe, only one out of four firms had received any type of public support at the time we conducted the surveys. This means that the large majority of firms around the world have faced the economic shock due to the COVID-19 pandemic without any type of public support. Panel (a) in Figure 1 shows the probability of utilizing public support across countries by income group, controlling for the fact that the survey was implemented at different stages of the pandemic as well as for sector and size fixed effects. One important caveat is that different countries had a different supply of public support, therefore we should expect lower access in countries where public support policies implemented were more limited. Still, the results show stark differences by income levels: the probability of receiving some public support is 11% in low income countries, 15% in lower-middle income countries, 30% in upper-middle income countries, and 53% in high income countries.

Figure 1: Access to public support.

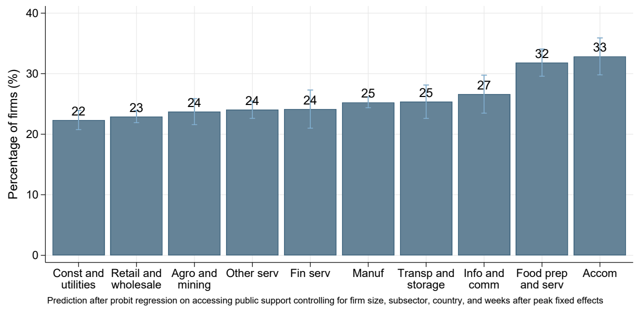
(a) Differences across income groups



(b) Differences across sizes.



(c) Differences across sectors.



[8] For additional discussions on observed policy responses see Freund and Mora (2020), IMF (2020), and ILO (2020)).

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The likelihood of receiving public support is also increasing in firm size (panel (b) in Figure 1), and this likelihood varies between 18% for micro firms and 30% for large ones. When looking at sectors, we do observe higher likelihood of receiving public support in some of the most affected sectors of the lock-down, such as accommodation (33%) and food preparation services (32%) (panel (c) in Figure 1). Finally, as expected, formal firms are more likely to access public support, albeit the difference is not large nor statistically significant.[9] While formal registration is needed for accessing some support programs, and utilization rates are low, informal firms are still able to access some support policies which highlights an effort by some government to provide universal support to the pandemic.

Table 1 breaks down access to policy into each group of programs, and shows that there are significant differences across income in terms of what policies firms are more likely to have received. The likelihood of receiving wage subsidies, access to finance, and payments deferrals dramatically increase with income, and high income countries are significantly more likely to offer every policy, but especially wage subsidies. Tax reductions and deferrals are the most common types of policies benefiting firms in low income countries with 5% of firms having access to them. The second most commonly accessed type of support in low income countries is access to finance, which is received with a probability of 2%. Similarly, the likelihood of receiving access to finance, tax support, and wage subsidies significantly increases with the size of the firm, whereas there are no statistically significant differences across sizes for monetary transfers and payments deferrals.

One key difference in the composition of support policies utilized are between formal and informal firms (Table 1). As expected, for the countries where we obtained information from informal firms, these are less likely to have utilized specific policy support, especially tax support, since depending on the measure of informality, most of these firms are not tax registered. On the other hand, informal firms have a probability of close to 5% and 3% of receiving monetary transfers and wage subsidies, respectively. This is consistent with some views that suggest the use of cash transfers to target informal firms, given the difficulties to effectively obtained information necessary for the targeting of other support policies.

[9] 16% for formal firms versus 13% for informal firms. See online appendix.

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Table 1: Specific policies received (fraction of businesses).

	Monetary transfer	Payments deferral	Access to credit	Tax support	Wage subsidies
Total	5.97	5.72	5.49	7.61	16.56
Low	0.65	0.84	2.34	5.27	0.53
Lower-Middle	3.71	3.95	4.63	6.15	3.55
Upper-Middle	3.18	5.14	5.13	5.43	18.45
High	13.26	11.16	7.79	13.22	36.78
Micro (0-4)	5.57	4.20	3.17	4.92	10.58
Small (5-19)	6.87	5.85	5.58	7.58	15.81
Medium (20-99)	5.08	6.05	6.75	8.49	18.90
Large (100+)	5.91	6.19	6.74	9.47	20.22
Formal	3.42	3.70	2.00	3.74	6.93
Informal	4.72	1.57	1.95	0.79	3.19
Agro and mining	6.79	4.90	6.26	7.24	17.05
Manuf	6.52	5.86	5.93	7.65	17.46
Const and untilities	5.32	4.10	4.42	6.65	14.15
Retail and wholesale	4.86	5.06	4.75	7.06	14.40
Transp and storage	6.74	5.74	6.18	7.10	16.61
Accom	7.40	8.44	7.86	13.33	25.21
Food prep and serv	8.28	9.01	5.88	9.81	22.02
Info and comm	6.76	7.69	5.37	8.53	17.56
Fin serv	5.39	5.54	6.95	6.91	15.53
Other serv	4.98	5.76	4.88	7.12	15.99
Demand shock	6.31	7.09	5.92	8.02	18.40
Production shock	6.30	5.67	6.92	7.43	16.61
Both	7.25	7.34	6.48	9.18	21.24
No shocks suffered	4.70	3.34	3.96	5.80	12.40
Non-Exporter	6.02	6.79	5.58	8.09	19.55
Exporter	6.80	6.84	6.17	9.26	20.19

Note: Average predicted means from separate Probits that control for country, size, sector, and timing of the survey. Computations use weights equal to the inverse of the number of observations in each country.

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4. The demand for policy support

While the previous section provided a granular view of the supply of policy support, this section analyzes the most demanded policy instruments, and how the demand for policies varies across country income groups, firm size, formality status, sector, exporting status, and transmission channels, relying on the response to the question "What would be the most needed policies to support this business over the COVID-19 crisis?"

Overall, access to finance (which includes deferral of credit payments, suspension of interest payments, rollover of debt, access to new credit, and loans with subsidized rates) and tax reductions and deferrals (which includes fiscal exemptions and reductions and tax deferrals) are the most demanded policy instruments with close to 50% of businesses reporting these instruments as the most needed interventions (Table 2). This is significantly larger than the share of firms reporting other policy instruments as most needed, such as payment deferrals (24%), monetary transfer (30%), and wage subsidies (24%).

Table 2 shows significant heterogeneity in terms of demand for policy instruments across income groups. The demand for wage subsidies significantly increase with the income level of the country. In contrast, the demand for monetary transfers, payments deferrals, and access to credit follow an inverted U shape with a higher demand in middle income countries, whereas tax reductions and deferral follows a U shape and is indeed the most demanded policy in low and high income countries. There are also significant differences in terms of the demand for policy support across firm size groups. Whereas the demand for tax reduction and deferrals and wage subsidies increase with size, the inverse is observed for monetary transfer, which is more likely among micro and small firms. Similarly, whereas the most demanded policy instruments for informal firms are monetary transfers and access to credit (with 60% of probability of each being the most needed policies), the most demanded interventions for formal firms are access to credit and tax support. There is little heterogeneity in terms of demand for policy support across sectors, exporting status, or channels through which the shock was transmitted, such as demand or production shocks.

Despite the heterogeneity observed across groups, we observe some common patterns. Access to finance and tax reductions and deferrals is among the top priority across firms from different groups, with the exception of informal firms. Moreover, the demand for wage subsidies tends to increase with country income level and firm size.

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Table 2: Most preferred policy support (fraction of businesses).

	Monetary transfer	Payments deferral	Access to credit	Tax support	Wage subsidies
Total	30.04	23.54	49.46	46.73	23.89
Low	9.53	8.43	25.65	50.38	14.19
Lower-Middle	29.80	26.02	59.16	46.07	16.64
Upper-Middle	36.06	23.77	49.37	46.52	41.96
High	31.52	15.00	25.39	65.24	45.99
Micro (0-4)	34.17	25.20	47.37	41.74	17.16
Small (5-19)	30.73	23.98	50.60	46.55	24.76
Medium (20-99)	26.11	21.33	50.96	49.58	27.06
Large (100+)	24.25	21.92	48.42	53.76	31.00
Formal	43.63	27.01	55.27	44.92	22.84
Informal	59.12	29.21	60.57	26.46	18.85
Agro and mining	33.57	18.85	52.11	37.53	21.02
Manuf	30.00	22.94	49.85	46.40	24.77
Const and untilities	29.12	19.99	51.47	46.51	21.82
Retail and wholesale	28.22	25.09	48.97	48.75	22.37
Transp and storage	30.75	20.82	49.50	46.75	25.57
Accom	31.32	22.41	47.17	48.57	31.55
Food prep and serv	33.49	31.48	49.44	45.88	23.62
Info and comm	29.82	24.83	47.79	52.06	22.11
Fin serv	24.78	20.92	48.69	50.10	21.85
Other serv	30.62	26.76	47.69	46.27	26.13
Demand shock	28.15	22.72	42.86	48.69	22.39
Production shock	26.81	24.71	52.39	46.33	21.39
Both	29.72	24.94	48.81	48.86	25.62
No shocks suffered	27.26	22.08	46.39	46.82	20.28
Non-Exporter	25.35	23.04	49.86	48.84	23.98
Exporter	25.34	21.97	47.71	50.22	27.40

Note: Average predicted means from separate Probits that control for country, size, sector, and timing of the survey. Computations use weights equal to the inverse of the number of observations in each country.

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5. Mismatch between demand for and supply of public support

Building on the previous sections, this section compares access to support with the firms stated preferences, that is, the potential mismatch between the demand for public policy and the access to these policies. Several elements can explain differences between policies demanded and received. First, some policies may not be available in the country due to fiscal constraints or preferences by the authorities. Second, firms may be discouraged from trying to access public support if application processes are too cumbersome or expensive, or if access is driven by opaque criteria and political connections. Third, there are less constraints to indicate policies that are preferred than policies that are received, which involves clear trade-offs in terms of budget.[10]

Our results show that, among firms in low income countries, tax support is at the same time the most preferred and most commonly received types of support policies (see Table 1 and Table 2).[11] Instead, when analyzing the responses of firms in lower-middle income countries, there is some alignment with tax deductions and deferrals, but a clear mismatch in the main intervention demanded and offered: access to credit is the most preferred policy, but tax support is the main mechanism of support offered, although only to 6% of businesses.

For upper middle income countries there is some alignment for wage subsidies, which at the same time rank high in terms of preferences among the firms but also are very commonly used. However, we identify a mismatch for tax deductions and access to credit, which appear to rank higher in terms of firms preferences but low in terms of utilization or access. A similar picture emerges for high income countries where there is a large mismatch for the demand for tax deferrals and access to these benefits, while there is a better alignment between the preference for wage subsidies and its utilization.

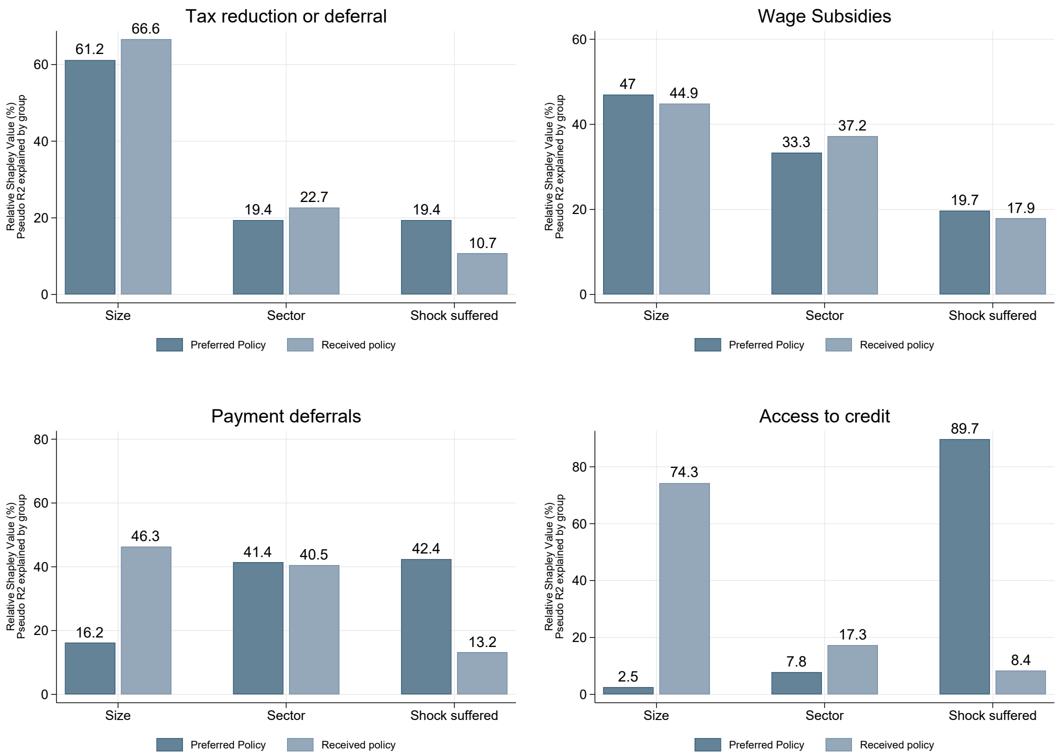
To investigate further the mismatch between the demand for policy and the public support received we implemented a decomposition exercise to understand what variables have higher explanation power to explain the likelihood for demanding or receiving the support. First, we ran a probit model for each type of policy instrument, including tax support, wage subsidies, payment deferral, and access to credit controlling for size group, sector of activity, shock reported by the firm (e.g. supply, demand, or both), and country fixed effects. We then ran a Shapley decomposition to estimate the relative contribution of each regressor variable, grouped by size, sector, and type of the shock. Figure 2 shows the results of this decomposition exercise, which are normalized to 1, excluding the contribution of country fixed effects. [12]

[10] In the BPS questionnaire, we asked firms to indicate up to three preferred policies.

[11] In this typology tax support encompasses both, tax exemption or reductions and tax deferrals.

[12] Absolute values of Pseudo R-squared vary by regression. Shapley values do not point the direction of the effect, but rather identify which grouping of variables contribute the most at explaining differences in both, preferences and access to policy.

Figure 2: (Mis)match of demand and policies received



The mismatch between the demand for policies and policies received is particularly larger for payment deferrals and access to credit. Overall, the results for received policies are consistent across the different instruments. Most of the variation on the likelihood to receive a public support associated with tax, wage subsidies, payment deferral, or access to credit, is explained by variation in size, followed by sector, and shock suffered. These results are also consistent with the fact that larger firms are more likely to receive support related to any of these instruments. A similar pattern is observed for demand for policy associated with tax support or wage subsidies. For both instruments, larger firms are more likely to report them as most needed policy. Yet, an inverted relationship is observed for access to credit and payment deferrals, where variation in the type of shock tend to have higher explanatory power for the demand for those instruments, followed by sector and size. This discrepancy is particularly relevant for access to credit.

6. Targeting (*mistargeting*) of beneficiaries

While the literature on social protection and transfers has focused extensively on the importance of targeting (see for example Hanna and Olken, 2018), evidence on private sector policies is more limited. Barrios et al. (2020) and Elenev et al. (2020) provide a framework for assessing the optimal targeting of loans during the pandemic and its role in extending liquidity support for small versus larger firm. The importance of targeting loans towards firms that critically need liquidity is also highlighted in Cororaton and Rosen (2020) who examine the characteristics of firm that have benefited from the United States' Paycheck Protection Program (PPP).[13] Funds disbursed through the Coronavirus Aid, Relief, and Economic Security (CARES) Act's PPP did not flow to areas more adversely affected by the economic effects of the pandemic, as measured by declines in hours worked or business shutdowns, but most likely to less hard hit businesses and locations (Granja et al., 2020). By comparison, the roll-out of a similar program in Italy appears to have been effective in reaching the smaller firms and those in more adversely affected areas (De Marco, 2020). In Portugal, policies related to debt moratorium, government credit lines, tax deferral and subsidized paid furlough was accessed disproportionately by lower productivity firms as these were the hardest hit by the crisis (Kozeniauskas et al., 2020). In China, although labor informality limited the extent of support to smaller firms, the regressive tax structure of social insurance contributions, and the greater labor intensity of small firms and sectors affected by COVID-19, still allowed tax breaks to deliver substantial benefits to vulnerable firms (Cui et al., 2020).[14]

In this section, we explore the relationship between the type and magnitude of shock experienced by firms and their access to public support. While many of the support policies were designed as universal, and any firm regardless of how impacted they have been could apply for support, it is important to measure whether support has benefited firms that did not need it - *mistargeting*. Specifically, we describe *mistargeting* as support that is going to firms that are not experiencing the pandemic shock. First, we use the information available on shocks, and distinguish between firms that do not experience a demand shock (i.e. whether demand has decreased) or a supply shock (i.e. closed premises or labor or input shortages), from those that experience at least one them. Second, we differentiate between firms that experience negative sales growth during the period and those that don't. Given that data was collected in most countries near the peak of the pandemic and sales referred to the level in previous 30 days, there was little or no time for policies to have immediate impact on our sales data (we explore the issue of policy effectiveness in more detail in the last section). As a result, our sales variable is more likely to represent the size of the demand shock experienced by the firm and an indication of the need of the firm for policy support.

Overall, we observe that firms that experience a larger shock in terms of sales are more likely to get support. Some of the sectors most affected by the pandemic such as accommodation or food preparation are also the ones with a higher likelihood of receiving policy support. Figure 3 confirms this result for all sectors plotting the correlation between average sector drop in sales and the probability of accessing policy. The negative slope is consistent with effective targeting.

[13] Among the set of eligible firms, beneficiaries tended to have more employees, have fewer investment opportunities and cash holdings.

[14] Targeting firms for support is problematic even during normal times (Grover and Imbruno, forthcoming) and the crisis accentuated this challenge further. In the United States, it has been found to be related to the significant heterogeneity across banks in terms of their capacity to disburse PPP funds (Granja et al., 2020) or the lack of awareness among small firms on the PPP program (Hum, 2020) or bureaucratic hassles and difficulties establishing eligibility (Bartik et al., 2020).

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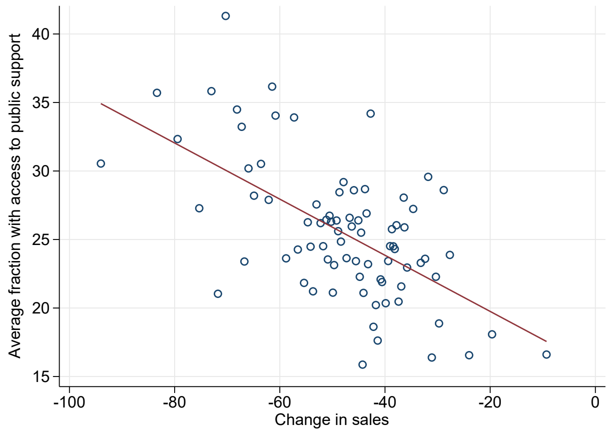
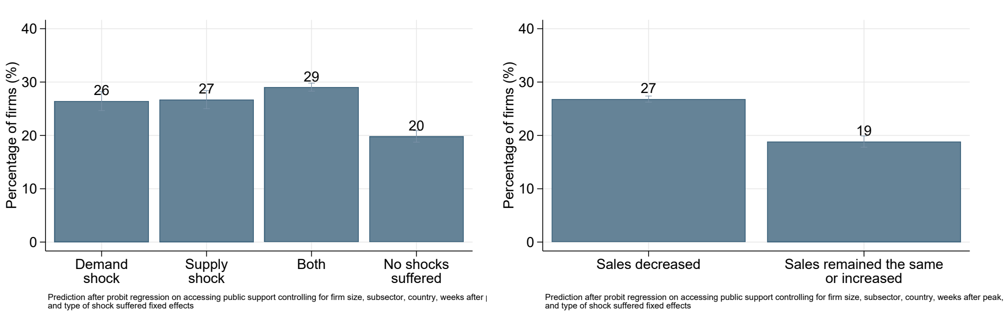
Figure 3: Correlation between change in sales and access to public support across sectors.



Note: For each sector in each country we compute the fraction of businesses with access to public support and the average change in sales. The figure is the binned scatterplot of this relationship after removing country fixed effects.

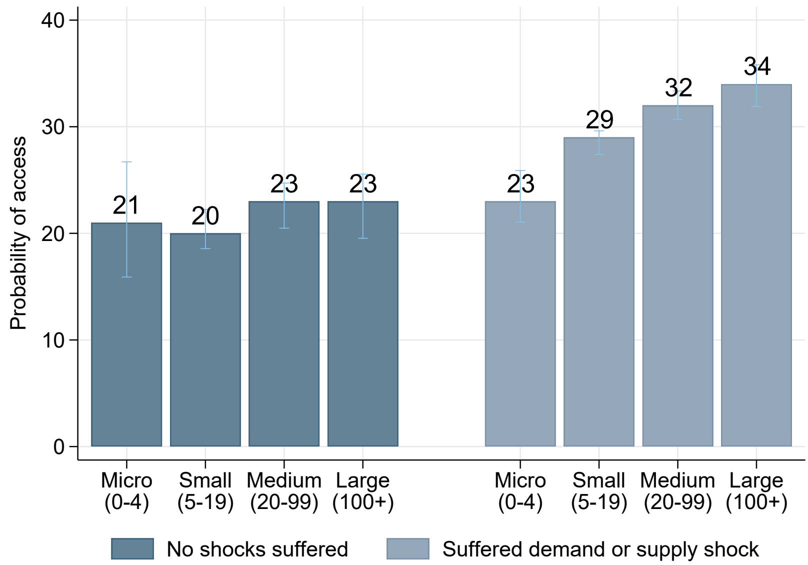
However, our results also show that a significant number of firms that did not experience any shock or sales drop as a result of the COVID-19 pandemic received public support. Figure 4 shows that while there is no significant difference in the probability of receiving public support for firms experiencing different types of shocks (26% for firms facing demand shocks only, 27% for firms facing supply shocks only and 29% for firms facing both); there is a non-negligible positive likelihood of near 20% of receiving public support for firms that declared not having experienced any shock. Also, the probability of firms that experience no change or increase in sales of receiving government support is 19%, not far from the 27% for firms that experience a reduction sales. In addition, we also find evidence of firms in need of support that do not receive it. Controlling for firm size, sector, country and severity of the crisis, the average drop on sales for those firms that receive support is -49% compared to an also large -43% for the group that does not receive any support.

Figure 4: Mistargeting on shocks and sales



The data suggest two main sources of *mistargeting*. A first source is related to access to support. Apedo-Amah et al. (2020) shows how smaller firms have been the most affected by the pandemic, but they have also been the less likely to receive any support. Figure 5 shows that while for those firms that do not experience a drop in sales it is hard to find differences in the probability of access, around 20%; for those that experienced the shocks, large firms have a much larger probability of getting support.[15] This may be driven by barriers to access policy support,[16] which are likely to be more binding for smaller firms (see next section), but also raise some potential political economy issues (Besley, 2007) on how support may be implemented.

Figure 5: Access, impact on sales, and firm size



A second source of potential *mistargeting* has to do with government capacity and the ability of public agencies to target beneficiaries. Figure 6 shows the probability of *mistargeting* - this is the probability of providing support to a firm that did not experience a negative shock relative to a firm that did experience a negative shock - across different countries; divided by their level of income (left panel) or the of their governance (right panel).[17] In order to control for the availability of support and a more universal approach folowed in soem countries, we use the share of firms that receive support in a country as an additional control. The results suggest that low-income countries are more likely to experience *mistargeting*. Figure A4 confirms this result, since the drop in sales in low-income countries is larger for the group without any support (-43% vs -36%), while in high-income countries supported firms experience much larger drops in sales (-34%) than those

[15] Figure A5 shows the analogous figure using whether the firms experienced drop in sales or not, with the same conclusions.

[16] We refer here both to information barriers as well as fixed costs to apply.

[17] Quality of governance is measured following (see Kaufmann et al., 2010).

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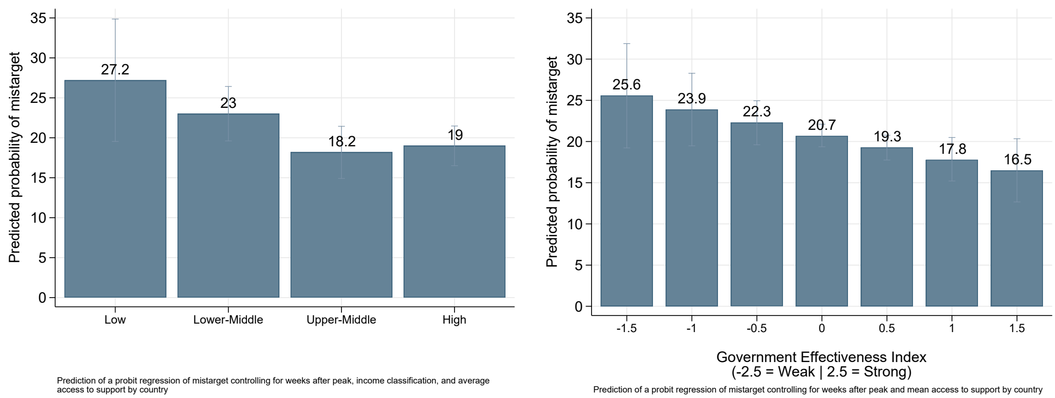
that did not get support (-21%). One channel through which this *mistargeting* may occur is via low implementation capacity and lack of good governance. The right panel in Figure 6 shows that *mistargeting* is decreasing in the quality of governance.[18]

Figure 6: Mistargeting by income groups and levels of governance quality



Summing up, while those firms that experience a more negative impact of the pandemic are more likely to receive support, there is some evidence that in the immediate aftermath of the pandemic crisis, governments have also supported a significant number of firms that did not experience any negative shock. This *mistargeting* is consistent with the fact that many policies were implemented very quickly, and targeting was not a big concern or too costly in the mind of policy makers, who mostly worried about the costs of inaction. But it is also explained by barriers to access and lack of implementation capacity. Going forward, as the crisis continues and puts pressure on limited fiscal resources, better and more careful targeting of beneficiaries and monitoring the access to policy support is critical.

7. Barriers to accessing public support: lack of awareness

It is important to understand why a large number of firms have been unable to access policy support measures announced and implemented in response to the crisis thus far. The majority of firms refers to lack of awareness as main reason for not receiving government support. There are, however, important differences across countries at different levels of per capita income. Controlling for other observable characteristics, there is an inverse relationship between the share of firms that report the lack of awareness for being unable to access government support and the income classification of countries. This share ranges from 74% in low-income countries, 52% in lower middle-income countries, 35% in upper middle-income countries to 12% in high-income countries (Figure 7). In high-income countries, 45% of firms cite ineligibility while 41% cite difficulty in

[18]The governance effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies (see Kaufmann et al., 2010).

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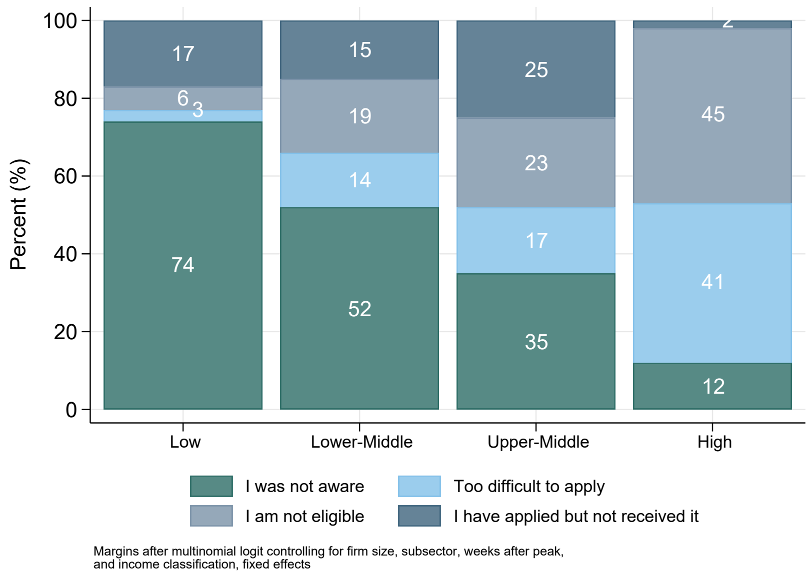
applying as the reason for not receiving government support thus far.

Figure 7: Reasons for not receiving public support across income group



The lack of awareness is somewhat lower in larger firms, but is the main reason for firms being unable to access government support programs in each size category – 58% of micro firms, 54% of small firms, 52% of medium-sized firms and 48% of large firms (see Supplemental appendix). Strikingly, there is little evidence to suggest that awareness of government support programs has increased since the peak of the crisis. Controlling for firm size, sector and country, approximately 56% of firms report the lack of awareness for being unable to access government support 1 week after the peak crisis but this remained unchanged even 16 weeks after the crisis, albeit with some fluctuations (see Supplemental appendix).

8. Policy interventions, expectations, and uncertainty

One of the most important effect of the COVID-19 crisis is that it was unexpected and significantly altered firms expectations and uncertainty (Lukas Buchheim and Link, 2020; Altig et al., 2020; Stephany et al., 2020). This issue is particularly relevant because it is informative for current and future policy decisions that need to understand the likely forward-looking scenarios facing by businesses going through a shock with large negative magnitude. For this reason, this section discusses how receiving different policies is correlated with future expectations and uncertainty.

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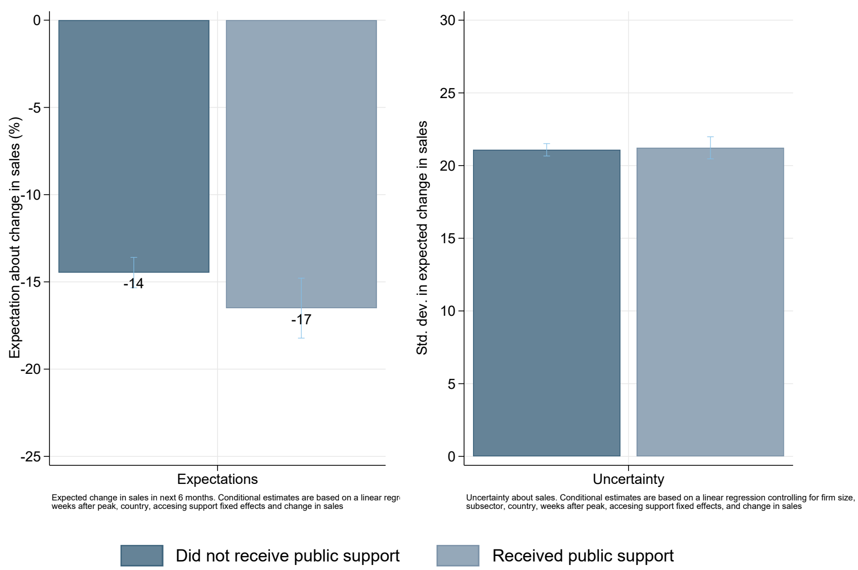
8.1 Policy interventions and expectations

The survey shows that across the board firms are expecting to sell less. In low income countries firms expect a decline in sales of about a third over the six months after the survey (compared to the same time period last year), and about a fifth to a quarter in lower middle income countries.[19] In addition, between a third to half of firms expect to fall in arrears in the coming six months or are already in arrears.

There is no robust and clear relationship between overall government support and the expectations about future revenues at firm-level. The data suggests that there are few differences in terms of revenues expectations between firms that received government support and those who did not. Averaging across countries, firms without government support report an expected drop of 16 percent, while firms with government support expect a decline of 14 percent (Figure 8), but this difference falls within the confidence interval. When controlling for observable characteristics such as size, sector and country, firms that have received government support expect lower sales than those who did not receive support, but these differences fall within the confidence intervals and are statistically insignificant. Since sales are to a large extent driven by demand and given that many policies are focused on covering acute cash shortfalls, we can expect government support to only play a small role in increasing sales at least in the short term.

Figure 8: Expectations and uncertainty about sales growth in next 6 months



There is a stronger relationship between government support and expectations around insolvency.

[19]These figures are higher than seen in high income countries. For example, the Federal Reserve Bank of Atlanta' Survey of Business Uncertainty reports expected drops in sales of between 0 and 3 percents for March and April 2020.

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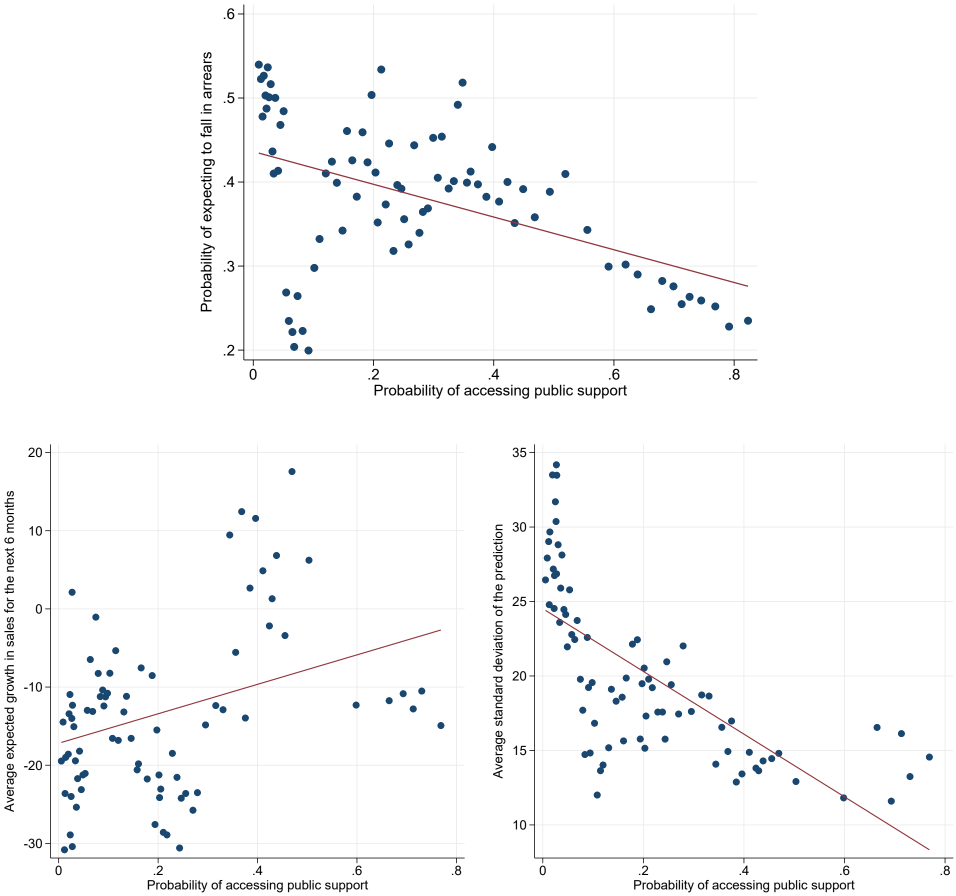
Using the predicted likelihood of whether a firm has access to support programs as a measure of the probability that a firm can access public support, Figure 9 shows that firms that are more likely to access government support are also those who report to be less likely in arrears or expect to fall in arrears. This relationship is robust to controlling for the change in sales experienced by the firm during the previous 30 days, indicating that having access to government support could play a key role in helping prevent firms from insolvency even when facing higher drops in sales.

Figure 9: Probability of expecting to fall in arrears, expectations and uncertainty about sales growth, and access to public support.



Note: Average predicted probabilities from Probits controlling for country, size, sector, and weeks before and after the peak of the mobility shock. Binned scatterplots.

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8.2 Policy interventions and uncertainty

Public policies can also play an important role in reducing the uncertainty faced by firms. This is a potentially important channel that could influence recovery because high degrees of uncertainty are likely to adversely affect firm investments and and incentives to innovate, by reducing the appetite for entrepreneurial risk taking (see e.g., Bloom et al. (2007)) and limiting jobs growth and reallocation. The survey provides some suggestive evidence that public policies could reduce uncertainty and improve growth expectations. The right panel in Figure 9 shows a negative correlation between the predicted probability that firms have access to public support programs and their uncertainty, measured as the average standard deviation of the firms' sales prediction based on (Altig et al., 2019). This cross-sectional correlation though may be driven by a lot of different factors, and as shown by Figure 8 when we control for size, country, sector and timing of the survey (relative to the peak of the crisis), and the size of the experienced drop in sales, we find that uncertainty is not any different between firms that received support versus those that did not.[20] While public policies may play an important role in reducing uncertainty towards the future it is possible that the large uncertainty associated with duration of the pandemic is at play during the COVID-19 crisis, which could explain our results. Applying to some of these public programs is costly and often complex, therefore firms that are more uncertain about the future could be more willing to incur these costs.

When digging further and breaking down the different types of policies, we confirm the results that uncertainty tend to be higher across firms receiving different types of support. However, these differences are not statistically significant as point estimates fall within the confidence intervals.[21]

9. Preliminary evidence on the effectiveness of policies

Despite the uniqueness of the current crisis, the impact of policy responses in past crises provides an important starting point to discuss the potential effectiveness of policies in the context of COVID-19. Fiscal stimulus in the form of temporary tax incentives for business investment has received some attention in the context of previous downturns (House and Shapiro (2008); Zwick (forthcoming)). In the aftermath of the December 2004 tsunami, Sri Lankan firms that received grants recovered profit levels substantially faster than those that did not (De Mel et al., 2012). Similarly, in Mexico, firms that were offered wage subsidies conditional on retaining workers in the aftermath of the global financial crisis, outperformed those that did not receive such benefits (Bruhn, 2020).

Evidence on the effectiveness of policies during COVID-19 has so far been mixed. Cui et al. (2020) and Chen et al. (2020) show that payroll tax mitigation and deferral of social insurance contributions in China bolstered the ability of firms to weather the economic downturn. However, Guerrieri et al. (2020) warn that in an economy where supply-side shocks directly influence aggregate demand and output, standard fiscal stimulus may be less effective than usual because the Keynesian multiplier feedback is muted due to shut-down of some sectors. Instead, monetary policy can have a magnified effects, by preventing firm exits and alleviating short-term liquidity constraints. Furthermore, studies have shown that financial support policies during COVID-19 have not been entirely effective

[20] This pattern is identical across countries with different income level, as well as different sizes and sectors as shown in our online appendix.

[21] Results available upon request.

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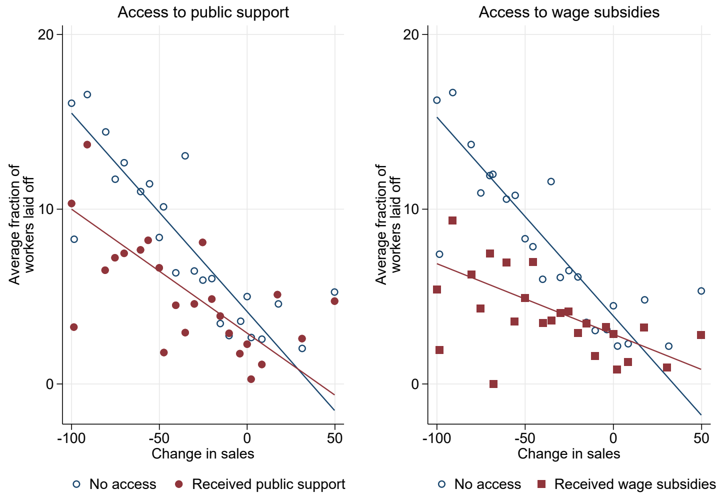
in alleviating SMEs' cash constraints or encouraging the reopening of small businesses, potentially due to difficulties in accessing policy-oriented loans and misallocation of credit. This has been true in China (Chen et al., 2020) as well as United States' PPP program (Granja et al., 2020; Chetty et al., 2020). During the current crisis, traditional macroeconomic tools – stimulating aggregate demand or providing liquidity to businesses – may have diminished capacity to restore employment when activity is muted due to health concerns (Chetty et al., 2020).[22]

To begin exploring the effectiveness of policies in mitigating the adverse micro-level impacts of COVID-19, we first focus on the employment response. Figure 10 shows the elasticity of laying off workers to the change in sales for firms which received public support (red line and dots) versus those that did not (blue line and dots). The results suggest that public support was successful in reducing the number of workers laid off in response to a drop in sales. In the same figure, in the right panel, we show that these results are driven by one specific type of policy, i.e. wage subsidies.[23] We also find that these results are driven by the impact of policies implemented in upper-middle and higher income countries[24] which is where the implementation of various forms of wage subsidies policies was more frequent.

Figure 10: Correlation between fraction of workers fired and change in sales.



Note: Binned scatterplots. Computation use weights equal to the inverse of the number of observations in each country.

[22]To help firms adjust and recover from the crisis, complementary investments may be needed to upgrade their capabilities and to mend broken supply chains. Some successful examples of firm upgrading programs include management consulting and technical skills training (Bloom et al. (2013); Iacovone et al. (2019); Anderson et al. (2018)), while supplier development and export promotion programs help alleviate information and networking frictions in accessing markets (Arráiz et al. (2013); Atkin et al. (2017)).

[23]To confirm that these differences are statistically significant we estimated at the firm level the conditional elasticity (controlling for country, size, sector, and timing of the survey) of the share of workers laid off to change in sales and we find that this elasticity is significantly smaller (less negative) than the elasticity of firms that do not benefit from policy support at the 5 percent confidence interval.

[24]These results are shown in Figure A3 in the online appendix.

Assessing rigorously the impact of policies is complex based on our cross-sectional data and the fact that a firm has access to policy support cannot be considered exogenous. Given our available information is not easy to identify an instrument that would work for different types of policies. For this reason, we present here some descriptive evidence based on simple OLS regressions but try to compare firms that are as comparable as possible. Specifically, we compare firms that applied and received policy support with those that also applied but did not receive it. Additionally, we always control for country, sector, size and time fixed effects, to make sure that we are narrowing our comparison to firms that are as similar as possible. We take these results as indicative evidence about the possible effect of policies while realizing we are not identifying precisely their causal impact as our results may be still be affected by a selection bias.

We focus on four firm-level outcomes of interest, some are outcomes that we expect could be directly affected by the policies (i.e. likelihood of laying of workers, expected future sales growth, likelihood of falling into arrears), while the remaining one could be at the same time affected by policy but also operate as mechanism that have in turn influences future firm-level outcomes (i.e. probability of investing in digital technology and solutions). The results are presented in Table 3 where we separate our analysis for different groups of policies (each policy is separately analyzed in different columns). We observe that certain group of policies appear to be more effective than others. Specifically, monetary transfers and access to credit which may be relaxing short-term credit-constraints and liquidity problem are correlated with higher future expected sales growth, as well as with higher probability of investing in digital solutions. Wage subsidies, in line with our prior and its stated objectives, is negatively correlated with the probability that firms laying off workers, while does not seem to significantly influence future sales or likelihood of falling into arrears in the coming months. Tax support[25] only appear to be positively correlated with future expected sales growth, while it does not appear to influence future likelihood of falling into arrears, and accordingly does not appear to be successfully correlated with reducing the likelihood that liquidity constraints turns into solvency problems. Finally, payments deferral[26] seems to be the least effective of all the policies with some marginal effect and positive correlation with the likelihood of expanding the use of digital platform.[27]

[25]Tax support includes fiscal exemptions, reductions as well as tax deferrals.

[26]This only refers to deferral of rent, mortgage, or utilities.

[27]The interested reader will find a more detailed and granular breakdown of individual policies in Table A1 from the supplementary material Online Appendix.

Table 3: Correlation between access to each policy and outcomes.

	Monetary transfer	Payments deferral	Access to credit	Tax support	Wage subsidies
Lays off workers (pr.)	-0.059	0.070	-0.028	-0.013	-0.094***
	(0.032)	(0.039)	(0.029)	(0.030)	(0.020)
Expects to fall in arrears (pr.)	-0.050	-0.047	0.004	-0.064	-0.018
	(0.049)	(0.061)	(0.046)	(0.044)	(0.039)
Expected sales growth (pp)	11.462***	6.908	8.193***	9.001***	2.711
	(2.275)	(3.953)	(2.257)	(2.657)	(1.479)
Inc. invest. digital sol (pr.)	0.153***	0.081	0.113***	0.006	0.026
	(0.035)	(0.042)	(0.028)	(0.031)	(0.024)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

10. Conclusion

Governments around the world responded to the deep economic impact of COVID-19 by rolling out more than 1,600 policy initiatives to support small and medium-sized businesses. While some learning from previous crises have proven useful in the initial response phase, policymakers and development practitioners have been faced with an acute lack of data and evidence on how to design and implement support policies.This lack of evidence is especially acute in developing countries. This paper addresses this gap by providing novel evidence using recently collected firm-level data covering more than 120,000 firms across 60 (mostly developing) countries.

The paper's results show that there are significant gaps to be addressed in order to improve the reach, targeting, and effectiveness of policy support. Smaller firms, especially those owned by women in sectors such hospitality, are facing some of the largest declines in sales *and* the most limited access to policy support – raising concerns about widening inequality. Similarly, the likelihood of receiving support for firms in poor countries is several times less than for similar firms in high-income countries. While governments appear to have prioritized minimizing exclusion concerns over strict targeting in the earlier stages of the pandemic, this has resulted in a large number of firms benefiting from public assistance without having experienced any adverse COVID-19 shock – an issue that will demand more attention as fiscal space becomes more constrained. Lastly, there is an indicative evidence that some types of policies (i.e. liquidity injections direct or through credit and wage subsidies) have been successful in mitigating liquidity constraints and reducing layoffs – but much more rigorous analysis will be needed to provide more precise guidance to policymakers.

Going forward we see four main avenues for future research. First, understanding better how firms manage to receive public support and the extent to which connections may explain access to public resources. Second, our results so far present some novel associations but we limited ourselves to mainly present conditional correlation. Future research, relying on additional data collection and stronger identification strategies, should address more carefully the question of the effect of

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receiving public support on subsequent firms results. Third, some of the policies being implemented may have important spillovers effects especially when targeted firms play an important role in supply chains and production, which will be an important area for future work to identify the systemic effects of policies being enacted. Finally, going forward it will be important to address the issue of policy misallocation and the risks that policies being enacted may inhibit prospects for recovery and future growth because of insufficient or incorrect targeting.

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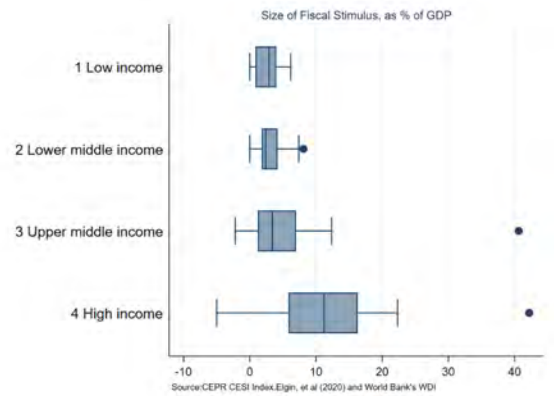
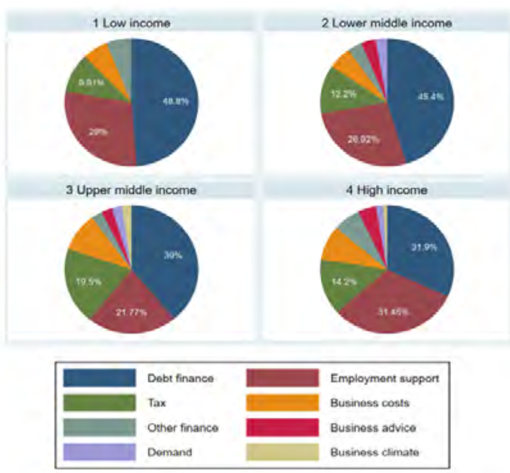
ONLINE APPENDIX: Supplementary Material

Figure A1: Size of fiscal stimulus.



Country income groups are defined according to the World Bank's World Development Indicators definition.

Figure A2: Policy responses by income groups.



Country income groups are defined according to the World Bank's World Development Indicators definition.

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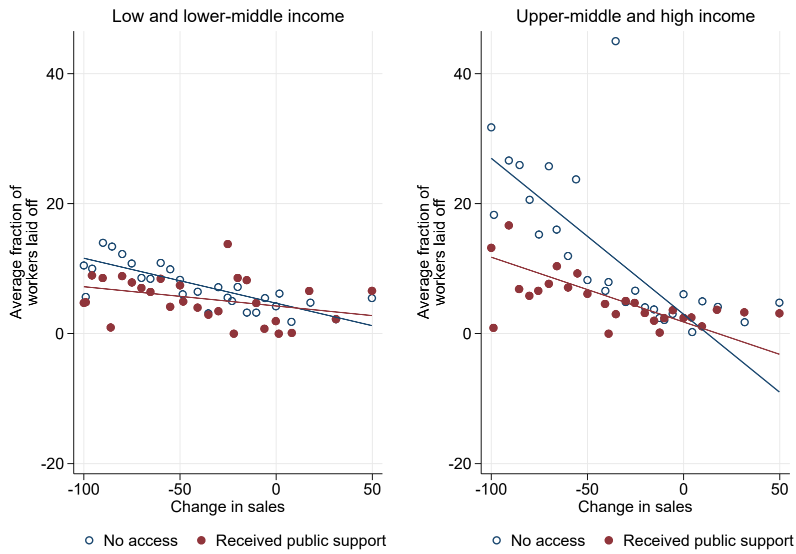
Figure A3: Correlation between fraction of workers fired and change in sales. Differences across income groups.



Note: Binned scatterplots. Computation use weights equal to the inverse of the number of observations in each country.

Figure A4: Access by size and decline in sales

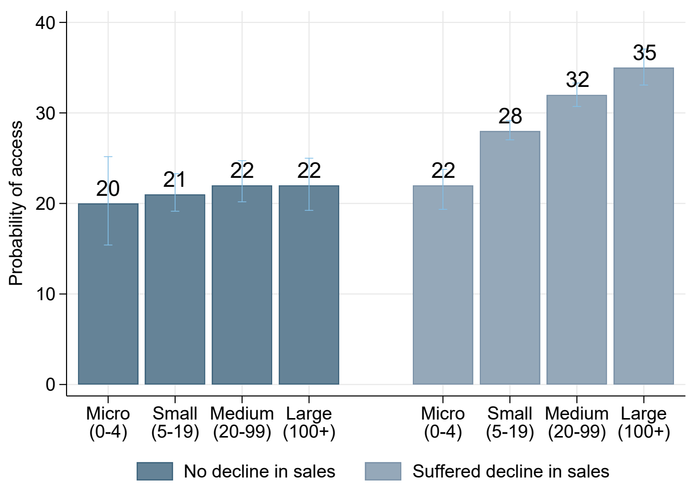


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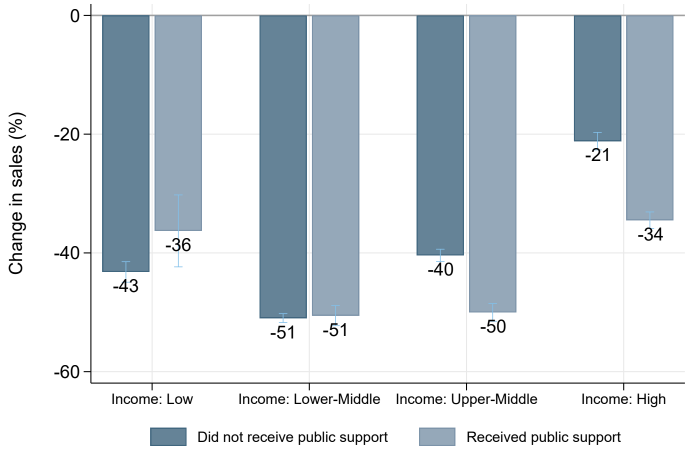
Figure A5: Access to public support and change in sales by income groups



Change in sales. Estimates are based on a linear regression controlling for firm size,
subsector, weeks after peak fixed effects and income classification interacted with accesing support

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Table A1: Correlation between access to each policy and outcomes. Individual instruments.

	Monetary transfer	Rent, utilities deferral	Credit payments deferral	New credit	Loans with subsidized rates	Fiscal exemptions or reductions	Tax deferral	Wage subsidies
Lays off workers (pr.)	-0.059	0.070	-0.019	-0.021	-0.088**	0.034	-0.031	-0.094***
	(0.032)	(0.039)	(0.027)	(0.052)	(0.033)	(0.054)	(0.025)	(0.020)
Expects to fall in arrears (pr.)	-0.050	-0.047	-0.035	0.037	0.021	-0.039	-0.106*	-0.018
	(0.049)	(0.061)	(0.052)	(0.065)	(0.078)	(0.058)	(0.046)	(0.039)
Expected sales growth (pp)	11.462***	6.908	7.542**	12.053**	4.216	8.270*	9.238***	2.711
	(2.275)	(3.953)	(2.655)	(3.888)	(3.495)	(3.589)	(2.758)	(1.479)
Inc. invest. digital sol (pr.)	0.153***	0.081	0.165***	0.108*	0.165***	0.033	0.017	0.026
	(0.035)	(0.042)	(0.032)	(0.050)	(0.047)	(0.050)	(0.029)	(0.024)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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The English patient: Evaluating local lockdowns using real-time COVID-19 and consumption data[1]

John Gathergood[2] and Benedict Guttman-Kenney[3]

Date submitted: 6 January 2021; Date accepted: 11 January 2021

We find UK "local lockdowns" of cities and small regions, focused on limiting how many people a household can interact with and in what settings, are effective in turning the tide on rising positive COVID-19 cases. Yet, by focusing on household mixing within the home, these local lockdowns have not inflicted the large declines in consumption observed in March 2020 when the first virus wave and first national lockdown occurred. Our study harnesses a new source of real-time, transaction-level consumption data that we show to be highly correlated with official statistics. The effectiveness of local lockdowns are evaluated applying a difference-in-difference approach which exploits nearby localities not subject to local lockdowns as comparison groups. Our findings indicate that policymakers may be able to contain virus outbreaks without killing local economies. However, the ultimate effectiveness of local lockdowns is expected to be highly dependent on co-ordination between regions and an effective system of testing.

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1 The views expressed are the authors and do not necessarily reflect the views of Fable Data Limited. We thank Fable Data Limited for sharing these data for research. Thanks to Constantine Yannelis, Chad Syverson, Kilian Huber, Pietro Veronesi, Scott Nelson, Pascal Noel, Peter Ganong, Jack Light, Hans-Joachim Voth, one anonymous referee and Chicago Booth Finance Student Brownbag audience for their feedback. We are grateful to Suraj Gohil, Debbie Mulloy, Fiona Isaac, Zina Papageorgiou and Sairam Kamath at Fable Data Limited and Lindsey Melynk and Rich Cortez at Chicago Booth for their help facilitating this research. This work is supported by the UK Economic and Social Research Council (ESRC) under grant number ES/V004867/1 'Real-time evaluation of the effects of Covid-19 and policy responses on consumer and small business finance'.

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1 Introduction

How can COVID-19 cases be contained without causing damage to the economy? This question dominates the thinking of policymakers, who face a seemingly uncomfortable trade-off between limiting virus transmission in the economy via reducing social contact, and maintaining economic activity which relies on social contact for the production and consumption of goods and services.

The first wave of COVID-19 in early 2020 saw most nations adopt stringent restrictions on social contact in almost all settings in order to contain the spread of the virus. These restrictions severely hindered the means of production and consumption in the economy, leading to large drops in output from a combination of the virus and such restrictions. However, recent improvements in testing and tracing leading to identification of clusters of cases in high-infection areas have facilitated a more targeted, localised approach to applying restrictions to social contact, known as "local lockdowns". This approach to limiting the spread of COVID-19 was identified early-on in the pandemic as a beneficial strategy.[1] In some countries – such as in the UK – governments have legal powers to implement such local measures, but this has been a source of political tension between local and national authorities.[2] The centralized UK approach offers a particularly interesting contrast to the US, where the policy response has limited national co-ordination – and none in regards to lockdowns.

In this paper, we are the first academics to use a new source of real-time and highly granular European consumption data. We combine these with data on coronavirus cases to analyse the impact of local lockdowns on both COVID-19 cases and local consumption. Using a difference-in-difference methodology, we estimate the impact of local lockdowns imposed in the late summer of 2020 on a series of UK cities, examining their ability to

[1] See https://medium.com/@tomaspueyo/coronavirus-the-hammer-and-the-dance-be9337092b56

[2] The legal power of the government in the UK to impose local restrictions contrasts with other nations, such as the US and Spain, where such measures can only be implemented by local governments. Nonetheless, both approaches have resulted in local resistance to such measures due to concerns of the adverse effects on local economies – with a standoff between local and national governments over locking down Madrid, anti-lockdown protests in London, Van Morrison releasing protest songs over the Northern Ireland local lockdown and some mayors and local governments demanding responsibilities powers and associated funding be delegated to them.

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contain of COVID-19 cases and how consumer spending responded.

Our study makes two main contributions. First, we introduce a new source of real-time, transaction-level consumption data – Fable Data – that can be used for economic research and to inform policymaking. These data contain transaction-by-transaction spending data, updated daily, for large representative samples of UK bank accounts and credit cards, with individual-level identifiers and geocode identifiers. We show these data are a highly correlated, leading indicator of official Bank of England statistics – data that are only available in aggregated form and with many months lag – in contrast to Fable Data which are available in real-time and disaggregated (correlation coefficient of 0.91 January 2018 - June 2020). These data are applicable to a broad variety of questions in the analysis of individual consumption behavior. They present a new opportunity for researchers to measure consumption in complementary and arguably more reliable ways than using data from consumption surveys, which has become less reliable in recent decades and has prompted a variety of initiatives aimed at improving the measurement of consumption (see Browning et al., 2014; Landais and Spinnewijn, 2020). These data show the UK's economic recovery in spending April to August 2020 had stalled in September and October.

Second, we advance understanding of the economic costs of mitigation strategies to contain the second wave of COVID-19. This user-case is economically important and policy-relevant to the time of writing, as policymakers around the world are grappling with how to both contain second or third waves of virus outbreaks and also to keep economic recoveries going. Local lockdowns are also a source of tensions between national and local governments and thus our research may help to inform such disputes. The UK local lockdowns we study apply to cities or small regions. They restrict how many individuals people can mix with, in what settings (e.g. restaurants) and under what requirements (e.g. outside, wearing masks). A key policy design was trying to enable people to keep consuming in COVID-19 secure settings while limiting their interactions in less secure settings (e.g. households visiting each others' homes). We show that UK local lockdowns to contain virus outbreaks – covering one in four people by September 2020 – typically

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turn the tide on rising COVID-19 cases though there is heterogeneity in such results.[3]

We do not find evidence such local lockdowns resulted in large spending declines: observing little, if any, declines. We use a difference-in-difference design that compares the evolution of daily consumption in an area subject to a local lockdown compared to a similar, nearby locality not subject to such restrictions. By using daily data we can precisely estimate our results relative to the timing of local lockdowns being announced. Our difference-in-difference approach is designed to be interpreted as descriptive not causal.[4] These data show – both for treatment and control localities – large drops in consumption when the March 2020 first virus wave and national lockdown occurred. We conclude there are little, if any, declines in spending from the local lockdowns: certainly not of the magnitude of the March decline. Estimates for the time-path of cases, in contrast, show that while COVID-19 cases typically continue to rise following the onset of a local lockdown (as measures take time to have effect) they then start to stabilize: indicating the local lockdowns had some short-term success.

While our evidence indicates some initial successes from local lockdowns, in late September and October 2020 the UK (along with many European countries) experienced a rapid, nationwide rise in COVID-19 cases (the cause of which is not yet clear). This has led to more restrictive regional measures being introduced in mid-October including shutting down businesses and before second and third national lockdowns were imposed in November 2020 and January 2021. The COVID-19 positive case rates accompanying these more recent lockdowns were far higher than the rates in the local lockdowns we examine in this paper.

Our study contributes to a burgeoning literature understanding the economic effects of COVID-19. A variety of early studies showed how the onset of COVID-19 dramatically changed consumption behavior. The first study to do so was Baker et al. (2020) using US

[3]https://www.bbc.com/news/uk-england-52934822

[4]We typically observe common pre-trends between control and treatment groups, however, we do observe noticeable increases in the number of positive COVID-19 cases for the treatment groups just before and after local lockdowns. The nature of local lockdowns explain this behavior – a key component is to increase testing capacity and thus the number of positive cases will be expected to rise. However, some areas subject to local lockdowns had rises that appear too large and sharp to be driven by differential testing and in such cases the control localities are less suitable counterfactuals.

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fintech data and following this Opportunity Insights (Chetty et al., 2020a,b) produced a dashboard using multiple data sources to track regional US consumption behavior alongside other economic indicators.[5] Beyond the US similar exercises have been carried out to understand household consumption in the early stages of the pandemic – showing remarkably consistent results (Andersen et al., 2020; Bounie et al., 2020; Bourquin et al., 2020; Campos-Vazquez and Esquivel, 2020; Carvalho et al., 2020; Chen et al., 2020; Chronopoulos et al., 2020; Horvath et al., 2020; Surico et al., 2020; Watanabe et al., 2020). Analysis of JP Morgan Chase data (Cox et al., 2020; Farrell et al., 2020) has described in detail how household balance sheets have changed as a result of the COVID-19 recession and how households have responded to fiscal stimulus. A variety of studies have examined the effects of the first set of lockdowns on economic behavior and evaluating the degree to which there are trade-offs between policy interventions attempting to contain the virus and economic damage (Aum et al., 2020; Beach et al., 2020; Barro et al., 2020; Coibion et al., 2020; Correia et al., 2020; Cui et al., 2020; Dave et al., 2020; Friedson et al., 2020; Hacioglu et al., 2020; Glover et al., 2020; Goolsbee et al., 2020; Goolsbee and Syverson, 2020; Guerrieri et al., 2020; Hall et al., 2020; Lilley et al., 2020; Miles et al., 2020; Jones et al., 2020; Toxvaerd, 2020; Wang, 2020).

2 Data

2.1 Consumption Data

We combine data on cases of COVID-19 identified by the UK's testing framework with consumption data provided by Fable Data Limited.[6] Fable data record hundreds of millions of transactions on consumer and SME spending across Europe from 2016 onwards.[7] Fable's transaction data are anonymized and available in real-time: our research access is with a one working day lag. Fable sources data from a variety of banks and credit

[5] https://tracktherecovery.org

[6] Daily COVID-19 case data by Local Authority District is available at `https://coronavirus.data.gov.uk/`. More information on Fable Data is available at `www.fabledata.com`.

[7] Commercial sensitivities mean we do not disclose the exact number of accounts and transactions available in the data.

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card companies: accounts cover both spending on credit cards and inflows and outflows on current (checking) accounts. Data is at the account-level and hence we can follow spending behavior on an individual account over time.[8] Fable data is similar to recently-available data sets from financial aggregators and service providers, but does not have some of the limitations of other datasets and uses anonymised customer data.[9]

For each spending transaction we observe a standard classification merchant category code for the spending type. Fable also produces its own categorizations of spending, utilizing the more granular information it has available from transaction strings. These data also differentiate between online and store-based transactions.

For each UK account we observe the postcode sector of the cardholder's address. In the UK, postcode sectors are very granular geographies: There are over 11,000 postcode sectors in the UK with each sector containing approximately 3,000 addresses. Where a transaction can be linked to a particular store, the full address of that store is available. Where a transaction is of a listed firm, Fable tags merchants to their parent groups and stock market tickers.

For this study we focus on transactions denominated in British pounds sterling on UK-based credit card accounts held by consumers.[10] The median and mean transaction values are £15 and £39 respectively.

Transaction-level spending data is highly volatile – even with such large volumes of transactions – and we observe strong movements at high frequency due to seasonality and day of week effects. We therefore follow an approach to smooth the transaction volumes over time as used by Opportunity Insights on similar US data (Chetty et al., 2020b,a): aggregating spending by day at the level of geography of interest, taking a seven day moving average and dividing by the previous year's value.[11] Finally, we normalize the

[8]In cases where one individual has multiple accounts, we cannot link multiple accounts in the data to the individual but can aggregate to a geographic region.
[9]Baker (2018) provides validation and application of US financial aggregator data. Financial aggregator data for the UK is widely shared for research purposes by MoneyDashBoard, UK-based a fintech (Chronopoulos et al., 2020; Bourquin et al., 2020; Surico et al., 2020). Bourquin et al. (2020) analyse the characteristics of MoneyDashBoard users.
[10]We drop 113 individual credit card transactions over £50k as such outliers are unlikely to be consumer transactions and may distort results for very small geographic regions.
[11]For 29 February 2020 we divide by an average of 28 February and 1 March 2019.

series setting an index to 1 using the mean value 8 - 28 January 2020. We also construct daily series using a 14 and 28 day moving averages in a analogous fashion.

2.2 Comparison with Official Statistics

Fable data have many useful features, such as timeliness (it is available the next working day whereas official statistics are typically available only with a lag of several months), geographic granularity (being available at a lower level than official statistics) and, transaction-level (enabling more flexible analysis than aggregated official statistics). These data can therefore potentially be used to construct leading indicators for policymakers and enable researchers to answer a broader set of research questions than was previously possible using prior data sources.

However, while these features are potentially valuable, their usefulness depends in part on how this data series relates to comprehensive, official data. To explore this, Figure A1, Panel A compares the time series of Fable Data UK annual changes in monthly credit card spending to the Bank of England series and shows they are highly correlated: correlations 0.91 (January 2018 to July 2020), 0.90 (January 2019 to July 2020) and 0.98 (January 2020 to July 2020). Bank of England data is only published in aggregated form monthly and with a lag (e.g. July's data was published at the start of September).

Figure A1, Panel B shows Fable data measures for 7, 14, 28 day moving averages – which can be calculated daily in real-time – compared to the monthly series (which requires waiting until month end). These daily moving averages show the sharp drop in consumption in March 2020 far earlier than the monthly series. We thus conclude that we can use these data as a reliable real-time predictor of official data and as a reasonable proxy for measuring credit card spending.

On aggregate we observe the sharp fall in UK credit card spending near the time of the spike in Covid-19 cases and national lockdown announcement on 23 March 2020 and then a fairly steady recovery May - August. Components of the national lockdown were ended in June and July but we do not observe rapid boost after these was lifted – indicating spending may have been suppressed by fear of the virus during this early

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phase of the pandemic. In September and October 2020, we observe these data to show that the recovery in spending since April 2020 has stalled and has started to decline.

In a companion paper (Gathergood et al., 2020) we use these same data to show the heterogeneous impacts of the COVID-19 crisis across UK regions and urban geographies: splits that are not possible using official statistics.[12]

3 Local Lockdowns

We use public data released by the UK government which details the areas affected by local lockdowns, including the dates of introduction and cessation of lockdown measures. Each week Public Health England publishes a COVID-19 Surveillance Report that includes 'The Watchlist' showing the incidence (and trend) of COVID-19 in local government areas (lower tier local authorities), whether household mixing is prohibited and lists areas on the watchlist.[13] Scotland, Northern Ireland and Wales have comparable data that we gather.[14]

Areas are added to the Watchlist considering a variety of metrics using professional judgment of UK public health officials according to the UK Government's COVID-19 Contain Framework'.[15] Areas on the Watchlist fit into one of three categories:

- **Concern Areas** - Local area is taking targeted actions to reduce COVID-19's prevalence (e.g. additional testing in care homes and increased community engagement with high risk groups).

- **Enhanced Support Areas** - More detailed plan agreed with the national team and with additional resources being provided to support the local team to control COVID-19 (e.g. epidemiological expertise, additional mobile testing capacity).

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[12]These figures were originally in an online appendix to the first version of this paper.
[13]www.gov.uk/government/publications/national-covid-19-surveillance-reports
[14]https://coronavirus.data.gov.uk/about-data#cases-by-lower-super-output-area-lsoa, www.opendata.nhs.scot/dataset/covid-19-in-scotland/resource/e8454cf0-1152-4bcb-b9da-4343f625dfef,www.health-ni.gov.uk/publications/daily-dashboard-updates-covid-19-september-2020,gov.wales/testing-data-coronavirus-covid-19-13-september-2020
[15]www.gov.uk/government/publications/containing-and-managing-local-coronavirus-covid-19-outbreaks/covid-19-contain-framework-a-guide-for-local-decision-makers

- **Intervention Areas ('Local Lockdowns')** - Divergence from the measures in place in the rest of England because of the significance of COVID-19's spread, with a detailed action plan in place, and local resources augmented with a national support to control COVID-19.

For this research we focus on local lockdowns. By September 2020, approximately one in four people in the UK were subject to a local lockdown. A key feature of such lockdowns is imposing restrictions on household mixing (e.g. preventing a tea party in someone's house) but permitting visits to more COVID-19 secure settings (e.g. having tea outdoor at a restaurant with strict hygiene and social distancing standards) in order to encourage consumers to keep spending while also trying to contain the virus. Across the local lockdowns there was variation in the how much household mixing was restricted (e.g. in Caerphilly residents were not supposed to leave nor new people come in).[16] This contrasts with the March 2020 lockdown where there was a stay at home order not only preventing household mixing but also closing all non-essential shops and banning public activities (e.g. sports).

There were also nationwide (including in areas subject to local lockdowns) government financial incentives to encourage consumers to spend for much of the period of time we study. The most notable of these were cuts to sales taxes (Value Added Tax, VAT) on food, accommodation and attractions from 20% to 5% from July 2020 until January 2021 and 'Eat Out to Help Out' scheme offering a 50% discount (up to £10 per person on food and non-alcoholic drink) for eating out Mondays, Tuesdays and Wednesdays during August 2020.

4 Methodology

We use a difference-in-difference methodology to estimate the relationship between local lockdowns and daily consumption. The use and challenges of difference-in-differences to estimate causal effects in COVID-19 is summarized in Goodman-Bacon and Marcus

[16]https://www.bbc.com/news/uk-england-52934822

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(2020). Our estimates provide a description of the evolution of COVID-19 cases and consumer spending pre- and post-lockdown on lockdown affected cities and comparison areas. We do not interpret our estimates as showing causal relationships - our comparison cities are not perfect counterfactuals for the evolution of COVID-19 cases or consumer spending in the absence of a lockdown.

We isolate the date local lockdowns were announced for each locality. There was great uncertainty in both where and when such lockdowns would be introduced and the precise restrictions that they would require - as reported in news reports at the time. Some anticipatory behavior is possible given the data on covid cases was regularly published and reported on but as the threshold for intervention was low areas often suddenly appeared subject to local lockdowns - most notably in the case of Manchester where the mayor and city council were taken by surprise.[17] Table A1 lists the timing of local lockdown announcements, the local authorities affected and the control group localities to compare against. Where there are multiple localities in the same area subject to a lockdown announcement on the same day we aggregate data (e.g. South and North Lankarkshire to Lanarkshire) into a single 'local authority group'. For some areas subject to local lockdowns (e.g. Belfast) no suitable control group city exists.

We display descriptive results for thirteen pairs of treatment and control localities – but primarily focus on the Manchester lockdown as that has a large sample, Liverpool offers a good control, the announcement was sudden and unexpected (being announced 9.15pm on a Thursday to coming into effect at midnight) and the case is particularly informative for considering the effects of a London lockdown.[18] The other areas studied that were subject to local lockdowns are: Aberdeen, Birmingham, Bolton, Caerphilly, Glasgow, Greater Glasgow, Lanarkshire, Leeds, Leicester, Newcastle, Preston and Wolverhampton. For consumption measures, we allocate spending based on cardholder's address except for considering large store chains where we estimate results based on store location. For COVID-19 cases allocation is as provided based on case reporting localities.

We first describe the time series for spending in these regions. A standard differences-

[17] https://www.bbc.com/news/uk-england-manchester-53592240
[18] https://www.bbc.com/news/uk-england-manchester-53592240

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in-differences approach uses a parsimonious regression estimation approach, such as that presented in (Equation 1). The outcome of interest $Y_{g,t}$ is offline credit card spending measured as changes in an index of yearly changes in 7 day moving average of spending. The unit of observation is a day (t) for each local authority group (g) either subject to the local lockdown or the control group to compare it to.

$$Y_{g,t} = \alpha + \beta\, Treat_g + \delta_t\, Treat_g \, * \, After_t + \gamma_t + \varepsilon_{g,t} \tag{1}$$

To explain our methodology we draw upon the example of Manchester. Manchester is the treated group ($Treat_g = 1$) subject to the local lockdown and we use a 'similar area' – Liverpool – as a control group ($Treat_g = 0$). These areas were chosen as cities of comparable size, in the same part of the country and showing similar pre-trends. $After_t$ is an indicator equal to one if the time period is after the local lockdown announcement. ($Treat_g \, * \, After_t$) is the interaction of the above two terms: it is an indicator equal to one if the time period is after the local lockdown announcement and the area is in the treated group. The difference-in-difference estimation approach allows for these areas to have different time-invariant relationships with consumption (α for Liverpool and $\alpha + \beta$ for Manchester) and γ_t is a series of daily dummies (with $t = -1$ omitted) to control for any common time-varying factors (e.g. national changes in COVID-19 cases, economic policies). δ_t provides an estimate for the relationship between local lockdown and consumption.

To better understand the local lockdowns we modify Equation 1 to estimate a dynamic specification creating weekly dummies ($After_{W,g}$) for the weeks preceding ($W \in \{-3, -2, -1, 0\}$) and following ($W \in \{1, 2, 3, 4\}$) the lockdown announcement where the omitted weekly dummy ($W = 0$) is the seven days preceding the local lockdown announcement ($t = -7$ to $t = -1$) and we use data up to four weeks pre- and post-lockdown (where available). We focus on a short time window given the volatile period we study the control groups are likely to become less suitable comparisons over time - including the subsequent government introduction of a system of tiered lockdowns in the autumn meaning no untreated control group remained. We estimate this using an OLS regression weighting

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observations by their 2019 resident population and cluster standard errors by region (with one observation per treatment group per day).[19]

$$Y_{g,t} = \alpha + \beta \, Treat_g + \sum_{W \neq 0} \delta_k \left(Treat_g \, * \, After_{W,g,t} \right) + \gamma_t + \varepsilon_{g,t} \tag{2}$$

We regard our estimation approach as providing informative, descriptive real-time evidence to inform policymakers. For these to be interpreted as causal effects for the effect of local lockdown on local spending would require a 'common trends' assumption that, for example, in the absence the Manchester local lockdown, consumption in Manchester would have followed the common trend to that in Liverpool. Such an assumption is unlikely to hold in these data - particularly over longer time horizons there may be spillovers between areas and other government measures being introduced - hence we interpret our short-term results as helpful descriptive evidence which might strongly suggest a causal relationship, due to what is known more generally about virus transmission and the efficacy of social distancing measures.

5 Results

5.1 COVID-19 Cases

We first examine the effects of local lockdowns on COVID-19 cases. The descriptive results are displayed in Figure 1. Vertical dotted lines display the timing of the national lockdown in March 2020 (affecting both treatment and control groups) and the local lockdown (day 0 when it was announced) that only affects the (yellow) treatment areas not the (black) control localities.

There are clear pre-lockdown differences in case data between lockdown areas and comparison areas, with lockdowns being introduced following a sharp increase in the case rate in each of the city graphs shown. The higher pre-lockdown case rate in lockdown areas may partially reflect a policy choice by health authorities whereby more tests are

[19]Resident population estimates are from Office for National Statistics (ONS).

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purposefully carried out in areas the government is considering introducing local lockdown restrictions. This is consistent with what we observe in COVID-19 positive cases as a percent of tests, however, such data are only available weekly and at a higher level of geographic region (upper rather than lower tier local authority) that does not align to areas subject to local lockdowns.

We observe cases continue to rise after the lockdown announcement – as would be expected given the disease's incubation period – but typically find that following the lockdown announcement the rise in cases ceases, case numbers peak and then level-off or decline. This therefore indicates that local lockdowns can be effective at containing COVID-19 outbreaks. However, while this is generally the case the results are heterogeneous with some exceptions to this – most notably Bolton and Glasgow where cases continued to rise after local lockdowns were imposed.

We estimate the relationship between local lockdowns and the evolution of cases using a difference-in-difference regression model. While our estimates should be interpreted as descriptive, we limit the sample for lockdown cases for which the pre-lockdown data indicates that the comparison geography appears to be a relatively suitable control for the treatment locality.[20] This leads us to drop Bolton and Leicester as there were far sharper rises in COVID-19 incidences before the lockdown than for their control groups. We also drop Aberdeen and Caerphilly as we have a relatively small number of transactions for these areas. Thus we have a remaining sample of six local lockdowns to study: Manchester, Birmingham, Glasgow, Greater Glasgow, Newcastle and Preston.

The dynamic regression results in Table 1 quantifies the relationship between local lockdowns and COVID-19 cases. In each case, the coefficient on the local lockdown dummy the first week post-lockdown is positive, and in most cases remains positive after two weeks, consistent with local lockdowns being imposed as cases rise towards a spike. The coefficients at subsequent time horizons fall, in the case of Manchester becoming negative in period one month after the imposition of the local lockdown.

[20]Roth (2018) highlights the limitations of relying on common pre-trends tests as evidence for common trends assumption for estimates to be interpreted as causal.

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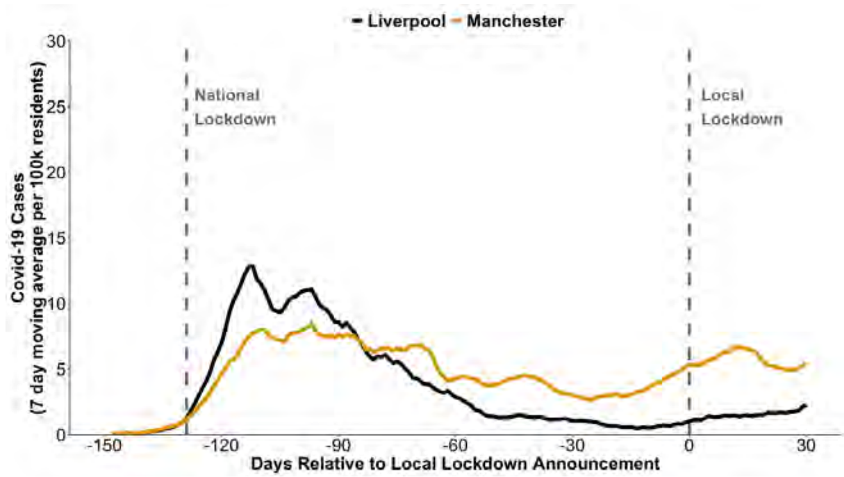
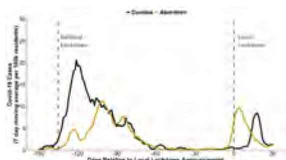
Figure 1: COVID-19 Cases in Lockdown Cities (yellow) vs Comparison Cities (black)

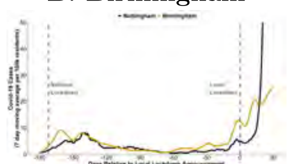
Manchester



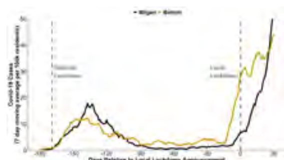
A. Aberdeen



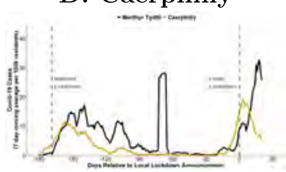
B. Birmingham



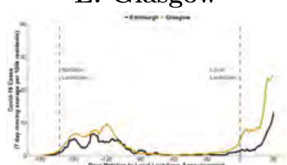
C. Bolton



D. Caerphilly

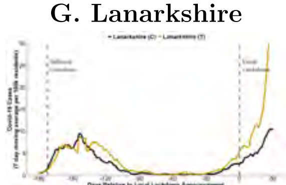


E. Glasgow

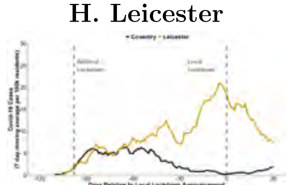


F. Greater Glasgow

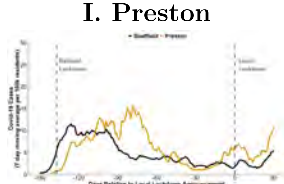
G. Lanarkshire



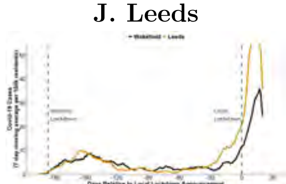
H. Leicester



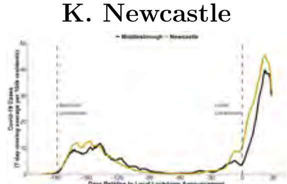
I. Preston



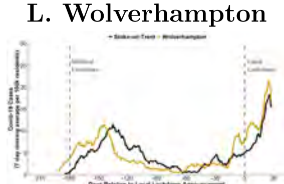
J. Leeds



K. Newcastle



L. Wolverhampton



Notes: 7 day moving averages. Data from Public Health England, Public Health Wales and Public Health Scotland.

Table 1: Dynamic Difference-in-Difference Estimate on COVID-19 cases per 100,000 residents (7 day moving average)

	Dependent variable:					
	COVID-19 cases per 100,000 residents					
	Manchester	Preston	Glasgow	G. Glasgow	Birmingham	Newcastle
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat{*}After_{\text{-}3}$	-2.015^{***}	-4.104^{***}	-1.171^{***}	-2.874^{***}	-4.129^{***}	-4.381^{***}
	(0.141)	(0.434)	(0.254)	(0.350)	(0.656)	(0.399)
$Treat{*}After_{\text{-}2}$	-1.475^{***}	-3.866^{***}	-0.927^{***}	-2.868^{***}	-4.836^{***}	-5.223^{***}
	(0.117)	(0.429)	(0.245)	(0.348)	(0.636)	(0.373)
$Treat{*}After_{\text{-}1}$	-0.850^{***}	-2.566^{***}	-0.866^{**}	-2.434^{***}	-3.795^{***}	-2.714^{***}
	(0.156)	(0.646)	(0.247)	(0.381)	(0.640)	(0.629)
$Treat{*}After_{1}$	0.393^{**}	0.343	3.439^{***}	1.194^{**}	0.560	4.801^{***}
	(0.119)	(0.521)	(0.596)	(0.359)	(0.652)	(0.963)
$Treat{*}After_{2}$	1.102^{***}	-1.054^{*}	4.251^{***}	-0.470	4.867^{***}	6.700^{***}
	(0.163)	(0.507)	(0.262)	(0.419)	(1.179)	(0.583)
$Treat{*}After_{3}$	0.710^{**}	-1.023^{*}	4.345^{***}	1.530^{***}	-7.994	3.446^{***}
	(0.261)	(0.497)	(0.455)	(0.406)	(6.084)	(0.466)
$Treat{*}After_{4}$	-0.496^{***}	-0.442	11.720^{***}	0.777	-87.443^{***}	
	(0.134)	(0.604)	(1.092)	(0.431)	(13.297)	

Note: *p<0.05; **p<0.01; ***p<0.001
OLS regression as specified in Equation 2 with fixed effects for areas and days. Areas are weighted by their 2019 resident population. Standard errors clustered at area level. Each column is for different area subject to local lockdown (with its nearby control area). Daily data for 4 weeks pre and post local lockdown(3 weeks post for Newcastle). Outcome is 7 day moving average of COVID cases per 100,000 residents in area from Public Health England and Scotland. Omitted category is week (days -7 to -1) preceeding lockdown.

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5.2 Consumption

Figure 2 summarizes credit card spending for the Manchester local lockdown compared to the Liverpool control group. Each panel displays different spending measures (using 7 day moving averages): A. all credit card spending, B. offline credit card spending C. food and beverage credit card spending D. credit card spending in large store chains. Our findings are consistent across these measures. A broader set of treatment and control groups pairs are displayed for the same credit card spending measures in Figure 3 (offline) and Annex Figures A2 (all), A3 (food and beverage) and A4 (large store chains, 14 day moving average) - due to smaller sample sizes in some of these areas the series are more volatile but show consistent results.

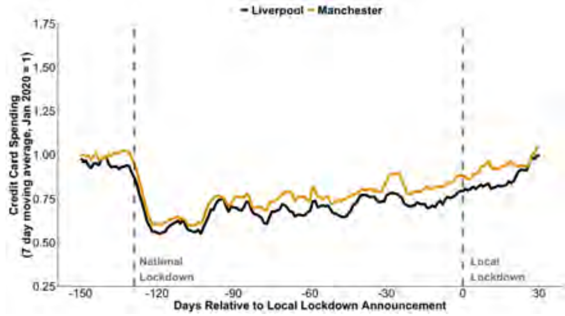
We highlight three features from these data. First, the treatment and control regions have similarly-timed and sized declines in spending in March 2020. The declines in consumption are economically large though we caveat that there is no control group unaffected by the virus or national lockdown to estimate the causal effects. Second, the treatment and control regions typically have similar trends in consumption in the lead up to the local lockdown being announced. These two features provide supportive evidence that our controls provide reasonable comparisons for the treatment areas.

Third, we observe little, if any, spending declines following the local lockdowns. While there is heterogeneity in results with differences in signs and statistical significance across pairs, a consistent feature is that we can rule out there being any economically large declines of the magnitude clearly observed (nationally or for these localities) in March 2020.

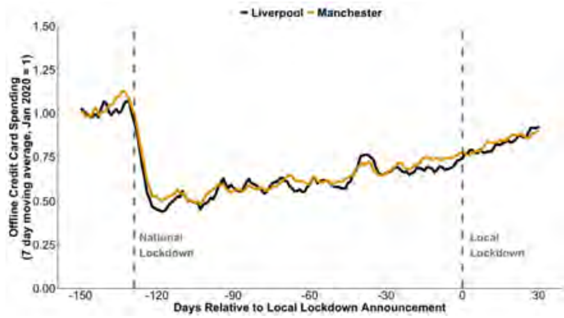
This descriptive analysis therefore indicates that local lockdowns are not having the large negative effect on consumption that the first wave of the virus and national lockdown did. Our dynamic regression results displayed in Table 2 also show this, however, we caveat it as in some weeks, in some lockdowns spending is lower. For example in Manchester, it is no more so than the difference observed pre-lockdown and certainly nowhere near the spending declines accompanying the March 2020 national shutdown.

Figure 2: Credit Card Spending in Manchester (yellow) and Liverpool (black)

A. Overall



B. Offline

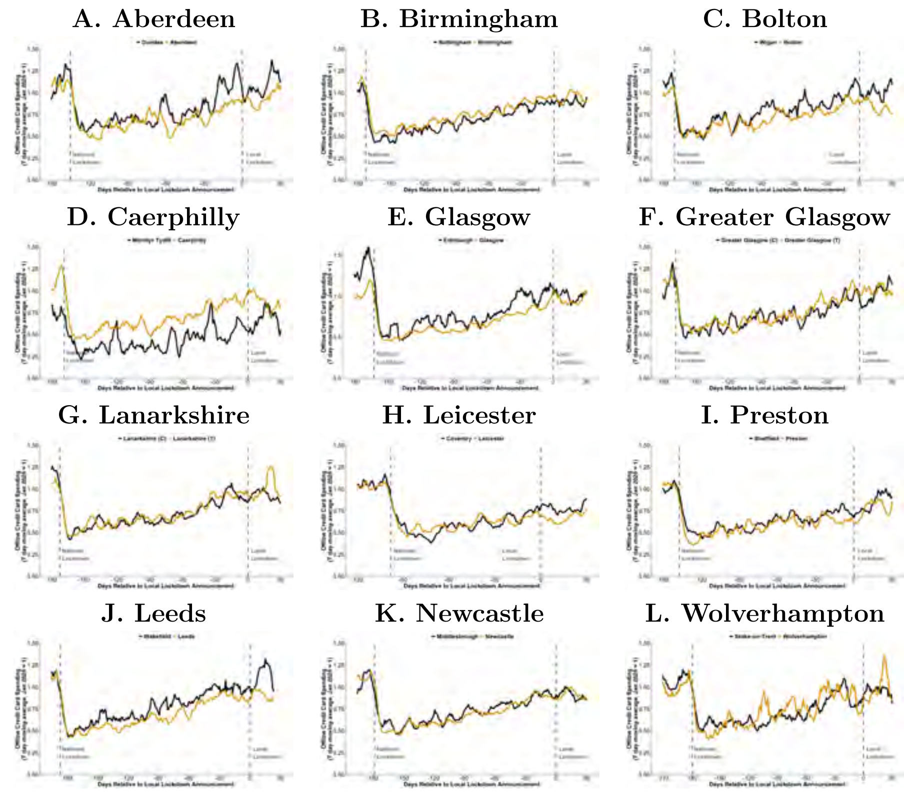


C. Food and beverage

D. Large store chains

Notes: Fable Data. Credit card spending measures use a 7 day moving average de-seasoned by taking ratio of the 7 day moving average a year prior. The series is then indexed to its moving average 8 - 28 January 2020. Panels A,B,C assign based on account-holder location. Panel D assigns based on large retail store chain location.

Figure 3: Credit Card Spending in Lockdown Cities (yellow) vs Comparison Cities (black)



Notes: Fable Data. Offline credit card spending is a 7 day moving average de-seasoned by taking ratio of the 7 day moving average a year prior. The series is then indexed to its moving average 8 - 28 January 2020.

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Table 2: Dynamic Difference-in-Difference Estimate on Offline credit card spending (7 day moving average)

	Dependent variable:					
	Offline credit card spending					
	Manchester	Preston	Glasgow	G. Glasgow	Birmingham	Newcastle
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat{*}After_{\text{-}3}$	-0.031^{***}	0.088^{***}	-0.062	-0.023	0.024	0.061^{***}
	(0.008)	(0.025)	(0.032)	(0.043)	(0.017)	(0.012)
$Treat{*}After_{\text{-}2}$	-0.015	0.020	0.072	-0.052	0.009	0.032^{**}
	(0.009)	(0.018)	(0.042)	(0.044)	(0.017)	(0.010)
$Treat{*}After_{\text{-}1}$	0.003	-0.090^{***}	0.023	-0.048	0.012	-0.029^{*}
	(0.007)	(0.023)	(0.043)	(0.064)	(0.014)	(0.011)
$Treat{*}After_{1}$	-0.049^{***}	-0.005	0.145^{***}	0.076	-0.019	-0.027^{**}
	(0.010)	(0.017)	(0.026)	(0.049)	(0.022)	(0.009)
$Treat{*}After_{2}$	-0.018	0.146^{***}	0.032	0.038	-0.059^{*}	0.001
	(0.011)	(0.031)	(0.027)	(0.046)	(0.028)	(0.017)
$Treat{*}After_{3}$	-0.028^{***}	0.056	0.154^{***}	-0.073	0.060^{*}	0.092^{***}
	(0.007)	(0.029)	(0.029)	(0.045)	(0.029)	(0.013)
$Treat{*}After_{4}$	-0.054^{***}	-0.090^{*}	0.111^{***}	-0.107	0.034^{*}	
	(0.011)	(0.034)	(0.026)	(0.055)	(0.015)	

Note: *p<0.05; **p<0.01; ***p<0.001
OLS regression as specified in Equation 2 with fixed effects for areas and days. Areas are weighted by their 2019 resident population. Standard errors clustered at area level. Each column is for different area subject to local lockdown (with its nearby control area). Daily data for 4 weeks pre and post local lockdown (3 weeks post for Newcastle). Outcome is Fable Data daily series index for 7 day moving average of offline consumer credit card spending. Outcome is de-seasoned by taking ratio of 7 day moving average a year prior and indexed (=1)to its moving average 8-28 January 2020. Omitted category is week (days -7 to -1) preceeding lockdown.

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6 Conclusions

We introduce a new real-time source of consumption data that we demonstrate is a highly correlated, leading indicator of official statistics, is also available at transaction level and can be disaggregated to produce daily measures across geographies.

Our analysis studies how consumer spending responds to UK local lockdowns using a difference-in-difference approach, comparing nearby cities or small areas. We do not find large spending declines in response to these local lockdowns. Instead we find little (if any) decline in local spending. To help interpret these estimates we observe that they are far smaller than the credit card spending declines observed nationally or for these localities during the combination of the first virus wave and national lockdown in March 2020. Using the same difference-in-difference methodology we find that these local lockdowns typically appear to turn the tide on rising COVID-19 positive cases.

We thus conclude that it appears possible for policymakers to use such local lockdowns restricting household mixing to contain COVID-19 outbreaks without killing local economies. However, we caveat this by noting that the effectiveness of such measures to mitigate the virus itself are expected to be highly dependent on an effective system of testing to isolate which regions to lockdown and contain infected individuals. It is also expected to depend upon co-ordination across regions by governments to ensure outbreaks in one area are contained and do not spillover into other areas.

While our evidence indicates some initial successes from local lockdowns, the UK (along with many European countries) experienced a rapid, nationwide rise in COVID-19 cases in late September and October following the end of the summer holidays, reopening of schools and universities (though the cause of the wave's sudden rise is not yet clear) indicating that its system of nationwide containment is not isolating cases early enough to be effective.

In Autumn and Winter 2020 a series of rapid COVID-19 outbreaks across the UK (and also other European countries) have since resulted in government imposing new, more restrictive systems of local and national lockdowns that includes forced business closures. In Gathergood et al. (2020), we document early evidence on how the measures

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implemented to November 2020 had unequal effects across UK regions. Whether measures being imposed in 2021 result in changes to consumption more like the first national lockdown or the local lockdowns we study here will have profoundly different implications for the UK economy's prospects and other countries facing virus outbreaks.

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Annex

Table A1: Local lockdown announcement dates, areas & controls

Announcement Date	Local Lockdown	Control
29/6	**Leicester** Leicester, Oadby and Wigston	**Coventry** Coventry
30/7	**Manchester** Manchester, Bury, Oldham, Rochdale, Salford, Salford, Stockport, Tameside, Trafford, Blackburn with Darwen, Bradford, Calderdale, Rossendale, Pendle, Hyndburn, Burnley	**Liverpool** Liverpool, Halton, Knowsley, St. Helens, Sefton, Wirral
5/8	**Aberdeen** Aberdeen City	**Dundee** Dundee City
7/8	**Preston** Preston	**Sheffield** Sheffield
1/9	**Glasgow** Glasgow City, East Renfrewshire, West Dunbartonshire	**Edinburgh** Edinburgh City, West Lothian
7/9	**Greater Glasgow (T)** Renfrewshire, East Dunbartonshire	**Greater Glasgow (C)** Iverclyde, North Ayrshire
7/9	**Caerphilly** Caerphilly	**Merthyr Tydfil** Merthyr Tydfil
5/9	**Bolton** Bolton	**Wigan** Wigan
11/9	**Birmingham** Birmingham, Sandwell, Solihull	**Nottingham** Nottingham
11/9	**Lanarkshire (T)** South Lanarkshire, North Lanarkshire	**Lanarkshire (C)** Stirling, Falkirk, Scottish Borders, Midlothian, East Lothian
11/9	**Belfast** Belfast	
16/9	**Rhondda Cynon Taf** Rhondda Cynon Taf	
17/9	**Newcastle** Newcastle upon Tyne, Gateshead, Sunderland, Northumberland, South Tyneside, North Tyneside, County Durham	**Middlesbrough** Middlesbrough, Redcar and Cleveland, Stockton-on-Tees, Darlington
18/9	**Liverpool** Liverpool, Halton, Knowsley, St. Helens, Sefton, Wirral	
18/9	**Wolverhampton** Wolverhampton	**Stoke-on-Trent** Stoke-on-Trent
18/9	**Lancashire** Chorley, Flyde, Lancaster, Ribble Valley South Ribble, West Lancashire, Wyre	
18/9	**Warrington** Warrington	
18/9	**Oadby and Wigston** Oadby and Wigston	
21/9	**South Wales (1)** Blaenau Gwent, Bridgend, Merthyr Tydfil, Newport	
21/9	**Northern Ireland** Rest of Northern Ireland (Belfast already in lockdown)	
25/9	**Blackpool** Blackpool	
25/9	**Leeds** Leeds	**Wakefield** Wakefield
25/9	**Stockport** Stockport	
25/9	**Wigan** Wigan	
25/9	**Welsh Cities** Cardiff, Swansea	
27/9	**South Wales (2)** Neath Port Talbot, Torfaen, Vale of Glamorgan	
29/9	**North Wales** Conwy, Denbighshire, Flintshire, Wrexham	

Notes: Lower tier local authorities listed. This does not include areas below the local authority level (e.g. Blaby, Charnwood, Carmarthenshire) where parts were locked down. 'Control' lists lower tier local authorities chosen as control groups: blank where not used for analysis because region is small and/or no suitable control area exists. Bolton announced and immediately introduced requirements on 5/9 but a full local lockdown was subsequently announced on 8/9.

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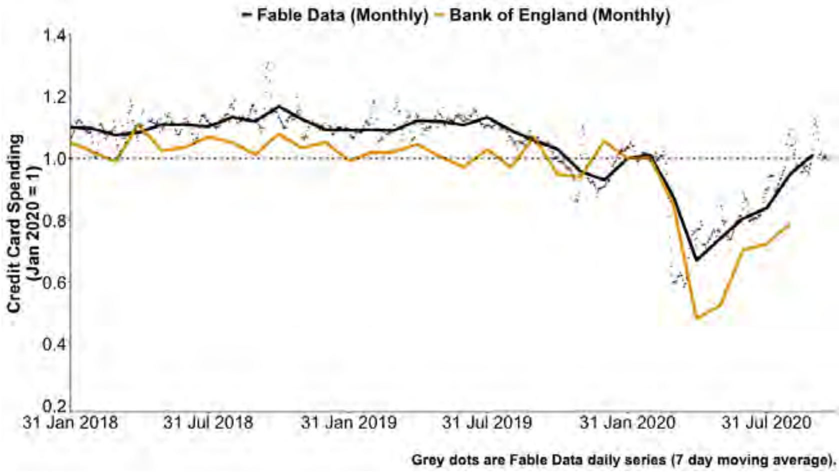
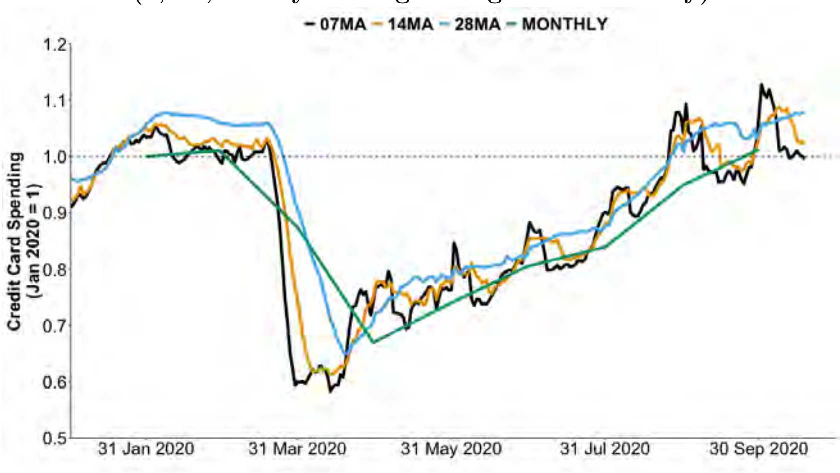
Figure A1: UK Credit Card Spending 2018 - 2020

A. Fable & Bank of England Monthly Data, 2018 - 2020

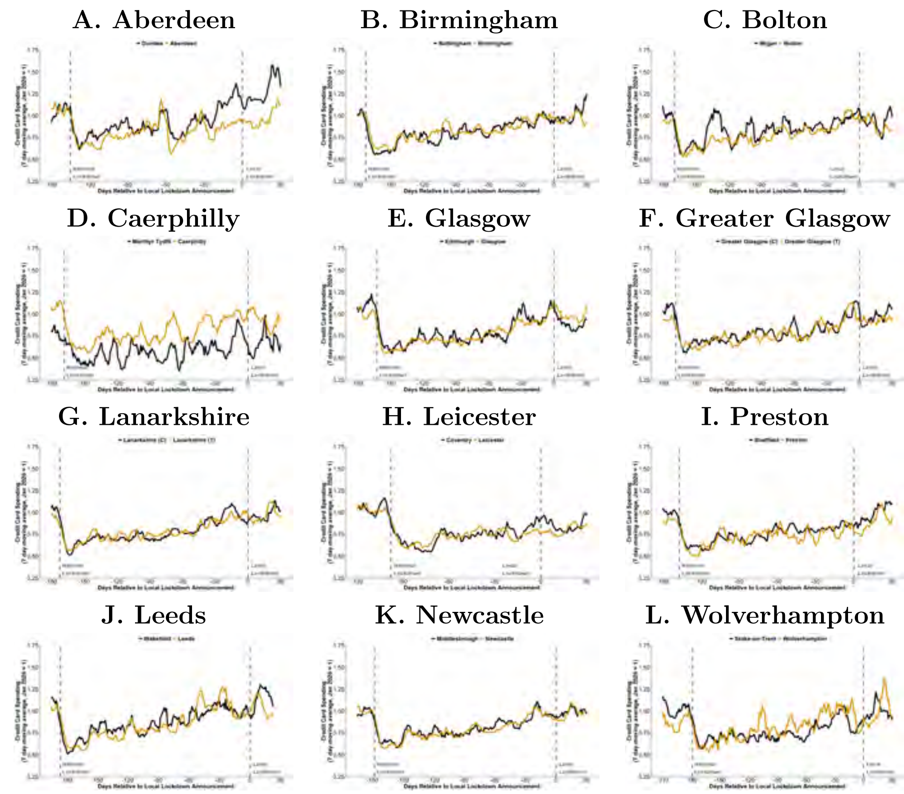


B. Fable Daily Data, 2020
(7, 14, 28 day moving averages and monthly)



Notes: Bank of England monthly data is derived from LPMVZQH (monthly gross credit card lending to individuals). Fable Data monthly series is indexed to January 2020. Fable Data 7,14,28 day moving averages are the daily moving average de-seasoned by taking ratio of the moving average a year prior. Each daily series is then indexed to its moving average 8 - 28 January 2020.

Figure A2: Overall credit card spending in areas subject to local lockdown (yellow) compared to control areas not locked down (black), 7 day moving average



Notes: Fable Data. Overall credit card spending is a 7 day moving average de-seasoned by taking ratio of the 7 day moving average a year prior. The series is then indexed to its moving average 8 - 28 January 2020.

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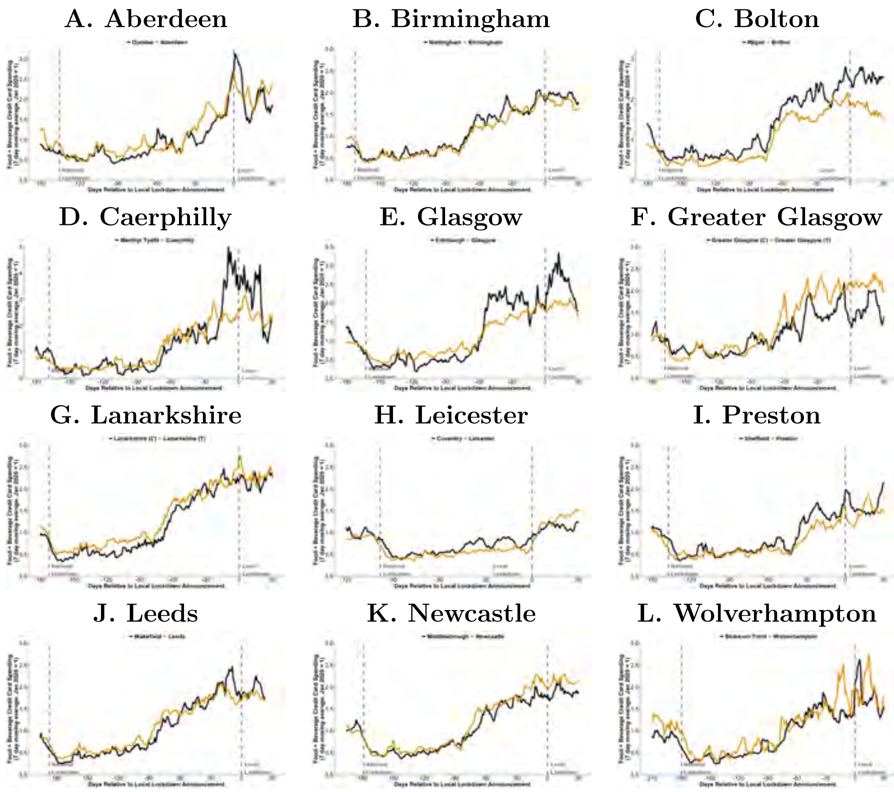
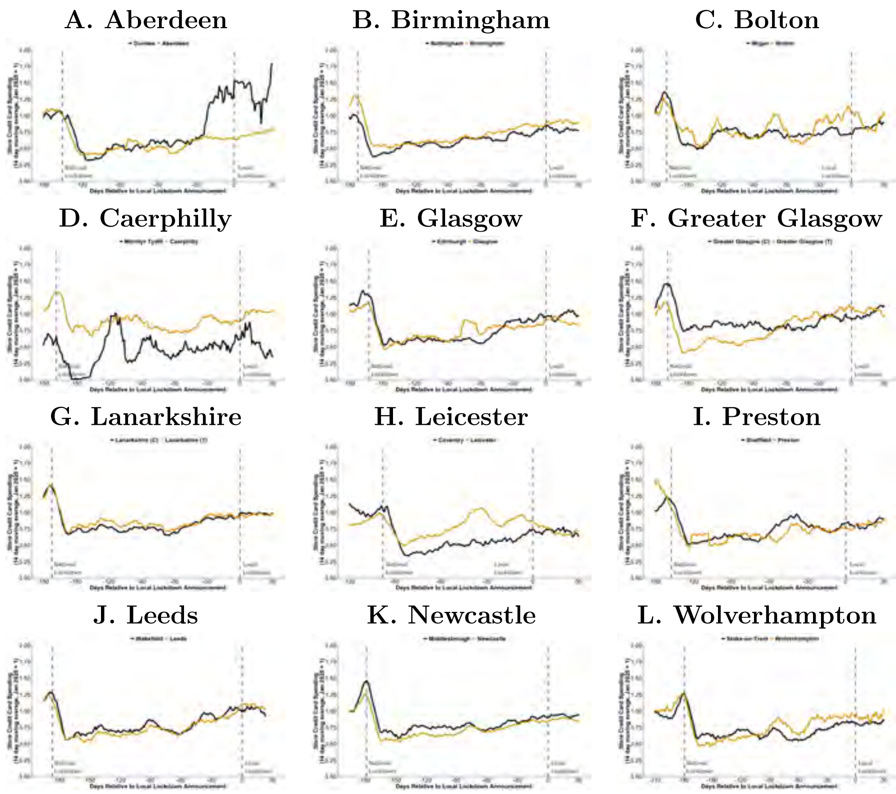
Figure A3: Food and beverage credit card spending in areas subject to local lockdown (yellow) compared to control areas not locked down (black)



Notes: Fable Data. Food and beverage categorization is based on Fable Data categorization using merchant category codes and transaction labels. Credit card spending is a 7 day moving average de-seasoned by taking ratio of the 7 day moving average a year prior. The series is then indexed to its moving average 8 - 28 January 2020.

Figure A4: Credit card spending in large store chains areas subject to local lockdown (yellow) compared to control areas not locked down (black), 14 day moving average



Notes: Fable Data. Store spending based on transactions tagged to large retail store chain locations. Credit card spending is a 14 day moving average de-seasoned by taking ratio of the 14 day moving average a year prior. The series is then indexed to its moving average 8 - 28 January 2020.

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Walking the tightrope: Avoiding a lockdown while containing the virus[1]

Balázs Égert,[2] Yvan Guillemette,[3] Fabrice Murtin[4] and David Turner[5]

Date submitted: 18 December 2020; Date accepted: 4 January 2021

Empirical work described in this paper explains the daily evolution of the reproduction rate, R, and mobility for a large sample of countries, in terms of containment and public health policies. This is with a view to providing insight into the appropriate policy stance as countries prepare for a potentially protracted period characterised by new infection waves. While a comprehensive package of containment measures may be necessary when the virus is widespread and can have a large effect on reducing R, they also have effect on mobility and, by extension, economic activity. A wide-ranging package of public health policies – with an emphasis on comprehensive testing, tracing and isolation, but also including mask-wearing and policies directed at vulnerable groups, especially those in care homes – offer the best approach to avoiding a full lockdown while containing the spread of the virus. Such policies may, however, need to be complemented by selective containment measures (such as restricting large public events and international travel or localised lockdowns) both to contain local outbreaks and because implementing some of the recommended public health policies may be difficult to achieve or have unacceptable social costs.

1 The authors would like to thank Laurence Boone, Luiz de Mello, Alain de Serres and colleagues from the Economics Department for useful comments and suggestions. Special thanks go to Théodore Humann for excellent research assistance. The views and opinions expressed in the paper do not reflect the official view of the OECD.

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Walking the tightrope: Avoiding a lockdown while containing the virus

1. Introduction and main findings

In most OECD countries, a combination of public health and containment measures, often involving a shutdown of major parts of the economy, was successful in reducing the spread of the new coronavirus (SARS-Cov-2) and associated diseases (Covid-19, used henceforth) in the first half of 2020. Having lifted many restrictions, the dilemma many policy-makers are now facing is how to deal with subsequent waves of infection without inflicting damage to economic activity on the scale that was so apparent from measures deployed in response to the first wave. The present study attempts to inform these decisions by examining country experiences during the period to mid-August at a daily frequency, with a focus on how the reproduction number, R, (representing the spread of the virus), and mobility (as a proxy for economic activity), respond to policy measures. The study makes use of a set of Covid-19 policy trackers maintained by the Oxford Blavatnik School of Government (Hale et al., 2020) as well as some complementary indicators developed specifically for this project.

Since the onset of the pandemic, parameterised epidemiological models (the so-called SIR models; Susceptible, Infected and Recovered) have been a popular tool to analyse disease dynamics (Anderson et al., 2020; Atkeson, 2020; Stock, 2020). These models can be used to shed light on the impact of physical distancing and other public health measures in containing a second wave of infections (Ferguson et al., 2020; Matrajt and Leung, 2020; Davies et al., 2020; Hornstein, 2020). SIR models rely on several parameters (for instance to quantify the impact of physical distancing on R), so their insights are only as good as these parameters are accurate. So far, however, most modellers have relied on past (mostly flu) epidemics to calibrate important parameters, while the current pandemic likely differs in important ways.

This study contributes to a burgeoning literature that seeks to quantify the impact of government interventions on disease progression and on mobility employing reduced-form econometric estimates for the Covid-19 pandemic itself. This literature has already shown that stricter lockdown policies go in tandem with a reduction in Covid-19-related deaths (Conyon et al., 2020). It has found strong evidence that banning mass gatherings is one of the most effective ways of taming the spread of the virus (Ahammer et al., 2020; Hunter et al., 2020; Weber, 2020). Similarly, air travel restrictions are found to be effective, especially those imposed on international flights and at the early stages of the pandemic (Hubert, 2020; Keita, 2020, Leffler et al., 2020). Stay-at-home requirements and workplace closures can also curb the propagation of the disease (Deb et al., 2020a; Hunter et al., 2020; Weber, 2020), as can the use of face masks (Hatzius et al., 2020; Leffler et al., 2020; Mitze et al., 2020). Nevertheless, the recent empirical literature has said little about the importance of testing and contact tracing policies, despite their prominence in SIR models, and the protection of the elderly population.

The findings of this paper are consistent with much of the above literature. Containment policies can successfully reduce the spread of the virus, but most -- in particular stay-at-home requirements, workplace closures and school closures -- have a substantial impact on reducing mobility and by implication economic activity. Most importantly, unlike earlier empirical studies, the results strongly support the view that testing, combined with effective contact tracing are key components of the post-lockdown strategy, especially at relatively low level of infections (OECD, 2020a). This corroborates a recent outbreak modelling study (Hellewell et al., 2020), which found that contact tracing and isolation would only contain outbreaks of Covid-19 if very high levels of contact tracing were achieved. This is also consistent with the view that testing and tracing is most effective in a low-infection environment, because contact tracing becomes increasingly difficult with higher levels of new daily infections (OECD, 2020a). Furthermore, estimation results suggest that mask-wearing and the protection of the elderly population in general, and those in care homes in particular, might play an important role in combatting the virus.

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Scenario analysis, based on empirical results in the paper, suggests that avoiding further lockdowns will require a wide-ranging package of public health polices, including a comprehensive regime of test, trace and isolation, mask-wearing mandates, isolation of those who are most vulnerable, and policies targeted at care homes. Moreover, unlike containment measures, these public health policies should have little adverse impact on mobility or economic activity. These findings are in line with and complement Acemoglu et al. (2020), who show in a multi-group SIR framework that the trade-off between mortality rates from the virus and economic damages can be attenuated if interventions are targeted on the most vulnerable individuals.

Public health policies may, however, need to be complemented by extending some containment measures, such as restrictions on large public gatherings or international travel, for which the aforementioned trade-off is most favourable. This is also because the most stringent and effective form of public health measures may have other costs, or be otherwise difficult to implement fully: many countries have struggled to roll-out comprehensive testing regimes; contact tracing becomes more difficult at higher levels of infections; banning visits to care homes is likely to cause distress for residents near end-of-life or suffering from dementia; and discriminating against certain groups, such as the elderly, who may be more vulnerable may also be difficult.

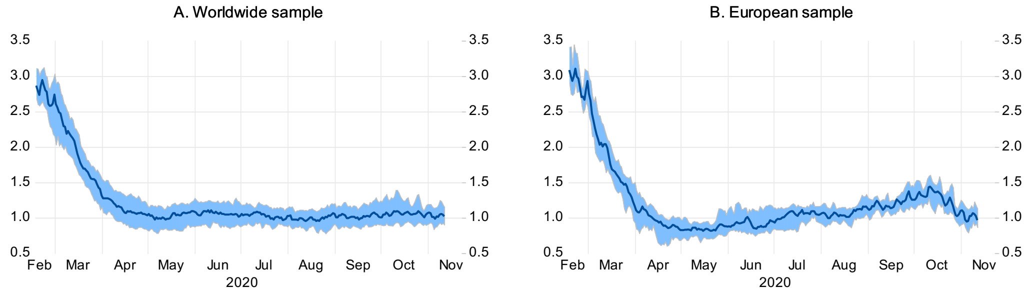
The remainder of the paper is organised around two equations estimated for a large sample of countries on daily data up to mid-August: the first explains the evolution of the reproduction rate, R, and the second explains mobility, as a proxy for economic activity. In the next section, various data issues underlying the empirical work are discussed (with further details on construction of R provided in Annex A). The policy implications of the estimated equations are then illustrated with a number of stylised policy scenarios, starting from the first outbreak of the virus, through full lockdown and, most importantly, exploring alternative strategies that would help keep the virus at bay.

2. Stylised facts about the reproduction rate, mobility and containment, testing and other public health policies

2.1. The reproduction rate

Estimates of the reproduction number, R, are constructed separately for each country using an approach adapted from the epidemiological literature and daily series on confirmed infections and deaths from the European Centre for Disease Prevention and Control (ECDC) (see Annex A for a detailed explanation). The median R estimate for a worldwide sample of approximately 70 countries fell from around 3 in February to around 1 in early May and has remained stable since (Figure 1, Panel A). This, however, hides considerable cross-country variation, with R nearing 1.5 in October in European countries, before a further set of major lockdown measures was implemented (Figure 1, Panel B).

Figure 1. Median and interquartile range for effective reproduction rate (R)



Note: The chart summarises trends in R for a selection of worldwide (Panel A) or European (Panel B) countries for which R can be computed over the full sample period.
Source: Authors' calculations derived from data on deaths and infections, see Annex A for details.

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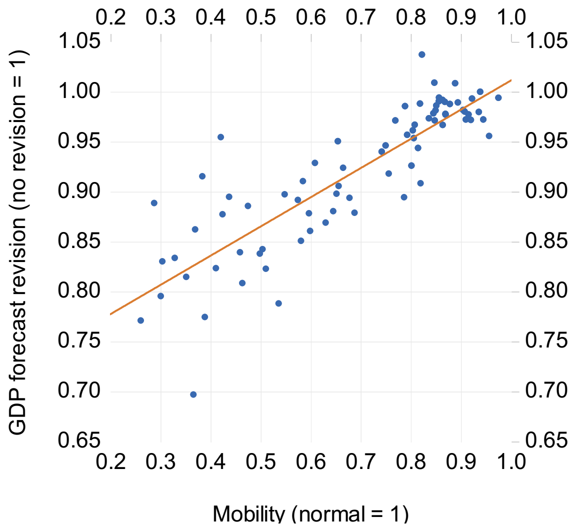
2.2. Containment policies and mobility

Many of the containment measures introduced by governments have had the objective of physical distancing. In the absence of a precise measure of physical distancing, high-frequency data on mobility provide a reasonable proxy. Such data are made available by Google, based on the movement of people with Android-based smartphones and with 'location history' turned on in their settings. The data are available for more than 130 countries at a daily frequency. The series measure the change in mobility from a same-day-of-the-week average in January and early February.[1] In many countries that imposed lockdowns, mobility fell by as much as 70% in late March and April, relative to the pre-lockdown period. There is a manifest link between mobility and GDP at a quarterly frequency (Figure 2) and mobility is used as a focus in the current analysis because good quality indicators of economic activity at a higher frequency with broad country coverage are not readily available.

Figure 2. Link between mobility and GDP forecast revisions at a quarterly frequency for 2020 Q1 and Q2



Note: The vertical axis is the ratio of the latest GDP estimate (or official outturn) to the projected level for the corresponding quarter in the December 2019 *OECD Economic Outlook*. Each dot represents a country/quarter combination. The chart covers OECD and BRIICS countries.
Source: Google LLC, *Google COVID-19 Community Mobility Reports*, https://www.google.com/covid19/mobility; OECD Economic Outlook No. 106 and 107 databases; and OECD calculations.

The empirical analysis here relies on a set of variables representing containment measures maintained by the Oxford Blavatnik School of Government (Hale et al., 2020), which in their original form are scored according to the degree of stringency or comprehensiveness with which they are applied. Eight categories of containment measures are distinguished (

[1] The mobility data are available for six location categories (grocery and pharmacies, parks, residential, retail and recreation, transit station and workplaces). This study works with a mobility index that is a linear combination of those six categories, giving greater weights to workplaces and transit stations. However, the six measures are highly correlated and a different weighting would have little influence on the results and conclusions.

Figure 3, Table 1), being variously scored 0 to 2, 0 to 3, or 0 to 4.[2] For the purposes of estimation, the cardinal value of these scores are ignored (as there is no reason, for example, to expect a policy with a stringency value of 3 to have treble the effect of a policy with a value of 1) and instead the same policy at different levels of stringency are included as distinct dummy variables (taking the value of zero or one). Subsequently, if the estimation does not deliver the expected ordinal ranking in coefficients (so that a more stringent application of a policy has a greater effect), the same coefficient may be imposed across different levels of stringency by combining policy variables.[3]

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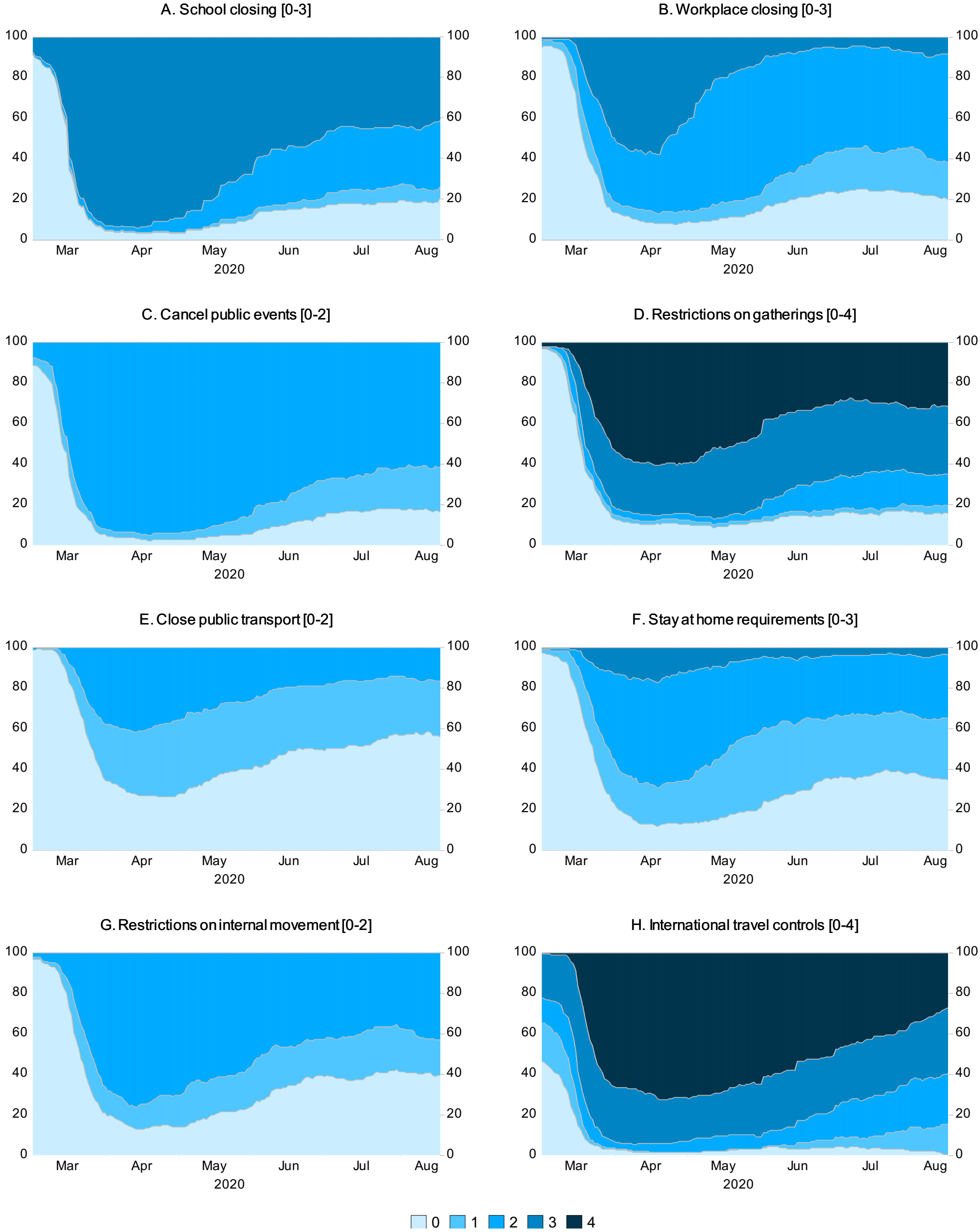
[2] The scoring of measures refers to their design, not necessarily how they have been applied. This represents a potential weakness as the variables do not capture how enforcement and abidance by regulations has varied across countries.

[3] Multicollinearity, implying problems in being able to separately identify coefficients on different explanatory variables, might be an obvious concern given that containment measures were often introduced simultaneously or very close together. However, the estimation here mitigates this problem by having a large country sample, daily frequency of observations and by distinguishing the stringency of such measures. Consequently, the correlations between containment measures variables used in the regressions are mostly far from unity. A possible exception is that there appears to be a degree of multicollinearity between variables representing school closure, workplace closure and stay-at-home requirements, which means some caution is required in interpreting specific coefficients as discussed in the text.

Figure 3. Percentage of countries at different stringency levels for containment policies according to the Oxford Covid-19 Government Response Tracker



Note: Stringency is evaluated as an ordinal index, with a higher number representing higher stringency. Each panel subtitle indicates the range for that category. The charts are based on the source's full country coverage for a given date, at most 185 countries.
Source: Authors' calculations based on Hale et al. (2020).

Table 1. Scoring of different stringency levels of containment policies according to the Oxford Covid-19 Government Response Tracker

Containment measure	Scoring of degree of stringency
School closures	1: Recommend closing
	2: Require closing (only some levels or categories, eg just high school, or just public schools)
	3: Require closing all levels
Workplace closures	1: Recommend closing (or work from home)
	2: Require closing (or work from home) for some sectors or categories of workers
	3: Require closing (or work from home) all-but-essential workplaces (e.g. grocery stores, doctors)
Cancel public events	1: Recommend cancelling
	2: Require cancelling
Restrictions on gatherings	1: Restrictions on very large gatherings (above 1000 people)
	2: Restrictions on gatherings between 101-1000 people
	3: Restrictions on gatherings between 11-100 people
	4: Restrictions on gatherings of 10 people or less
Close public transport	1: Recommend closing (or significantly reduce volume/route/means of transport available)
	2: Require closing (or prohibit most citizens from using it)
Stay at home requirements	1: Recommend not leaving house
	2: Require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips
	3: Require not leaving house with minimal exceptions (e.g. only once a week, or one person at a time)
Restrictions on internal movement	1: Recommend not to travel between regions/cities
	2: Internal movement restrictions in place
International travel controls	1: Screening
	2: Quarantine arrivals from high-risk regions
	3: Ban on arrivals from some regions
	4: Ban on all regions or total border closure

Note: Not shown in the table, but "No measures" or "No restrictions" are always scored 0.
Source: Hale et al. (2020).

2.3. Test, trace and isolation policies

Evidence for a large cross-section of countries suggests a negative correlation between the number of tests and mortality rates (Liang et al., 2020). Testing can break the chain of transmission and prevent the local outbreak of new infections, but to be effective requires the scale of testing to be ramped up quickly, a high accuracy of testing and the ability to carry out testing swiftly, which many countries struggled with during the first wave of Covid-19 (OECD, 2020a).

It has been argued that repeated mass testing coupled with the isolation of the infected would eradicate the virus without reliance on contact tracing (Taipale, Romer and Linnarsson, 2020). China has demonstrated the potential for mass testing in the city of Wuhan in May, with up to 1.5 million tests being processed in a single day (New York Times, 2020a). In early November 2020, Slovakia tested two-thirds of the country's population using rapid antigen tests (Euronews, 2020). Antigen tests provide results more quickly (within 30 minutes) compared to conventional PCR tests. While they are less accurate and miss some of the asymptomatic cases, experts argue these cases are likely to be less infectious (New York Times, 2020b).

Unless testing can be carried out quickly and on a truly mass scale, testing also needs to be accompanied by tracing the persons who have been in contact with the infected person. The effectiveness of testing and tracing crucially depends on the coverage of the contact persons. Its success also hinges on the speed with which the tests are carried out and the contact persons identified, tested and isolated if tested positive (Hellewell et al. 2020). Scenario analysis shows that a high level of testing in tandem with widespread and timely contact tracing and isolation may prevent a

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subsequent surge in infection rates (Panovska-Griffiths et al. 2020). Scaling-up contact tracing is difficult, but not impossible. ECDC (2020c) recommends: the use of well-trained non-public-health staff and volunteers; repurposing existing resources such as call centres; and using new technologies such as contact management software and mobile apps. Widespread testing and contact tracing is considered by many as a crucial part of policy packages during the de-confinement phase (Aleta et al., 2020; ECDC, 2020c).

To capture the effect of track-and-contact-trace policies, the policy indicators from the Blavatnik School of Government at the University of Oxford (Hale et al., 2020) are used, which in their original form are also scored according to the comprehensiveness of the testing or tracing regime (Table 2). They suggest there was a substantial improvement in the number of countries increasing the extent of their test and trace policies in the 2-3 months from March, but further increases since then have been modest (Figure 4). However, for the estimation work reported here, the cardinal values of these scores are again ignored and instead different dummy variables are used to represent test-and-trace variables at different degrees of comprehensiveness. An additional variable, constructed by the authors and described below, considers the importance of specific testing in care homes (Table 3). However, an important limitation of these indicators is that none cover issues of timing which can be key to a successful strategy: tests need to be done quickly and with a minimum delay before the results are available and then contacts need to be traced quickly. On the other hand, many issues relating to testing, including timing, may be easier when the level of infections is lower, and this can be readily tested in the empirical framework.

Table 2. Scoring of the Oxford testing and contract tracing policy variables

H2 Testing policy[1]: Who can be tested?
0: No testing policy
1: Only those who both (a) have symptoms AND (b) meet specific criteria (e.g. key workers, admiitted to hospital, came into contact with a known case, returned from overseas)
2: Testing of anyone showing COVID-19 symptoms
3: Open public testing (e.g. "drive through" testing available to asymptomatic people).
H3 Contact tracing: Are governments doing contact tracing?
0: No contact tracing
1: Limited contact tracing - not done for all cases
2: Comprehensive contact tracing - done for all identified cases.

Note: (1) Testing variable relates to policies testing for infection (PCR test), not to policies testing for immunity (antibody tests).
Source: Hale et al. (2020).

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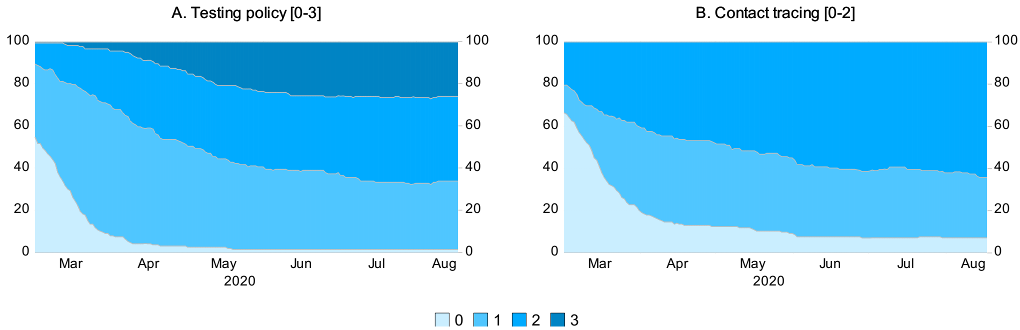
Figure 4. Percentage of countries at different stringency levels for testing and contact tracing policies according to the Oxford Covid-19 Government Response Tracker



Source: Authors' calculations based on Hale et al. (2020).

2.4. Shielding the elderly

The elderly population is especially vulnerable to Covid-19 with much higher mortality rates than other demographic groups. A particular concern is that mortality rates have been very high in care/elderly/retirement homes (henceforth referred to as 'care homes') in some OECD countries (ECDC, 2020b; Gandal et al. 2020). Evidence, concerning experience in care homes with managing influenza outbreaks as well as the current pandemic, suggests that improving hygiene, including regular hand sanitising and disinfection at the establishment level (Koshkouei et al., 2020), as well as limiting the migration of staff across different care homes help to reduce infection rates substantially (Koshkouei et al., 2020; Chen et al., 2020), although the latter may be difficult given widespread staff shortages.

Empirical evidence is less clear-cut for testing staff and residents, and limiting visitors, even though these measures could be part of any infection management. Testing in care homes is particularly appealing, especially if testing capacities are limited. Testing should target potential super-spreaders (e.g. healthcare professionals) or groups of people who may find it difficult or impossible to comply with physical distancing, such as the elderly in packed care homes where several people live in the same room (OECD, 2020a). Some argue that these high-risk groups should be regularly tested even in the absence of symptoms (Grassly et al., 2020).

The current empirical work tests for the effectiveness of three types of government policies using variables constructed by the authors: firstly, recommendations to persuade the elderly to stay at home; secondly, restricting visits to care homes; and thirdly, testing of residents and/or staff of care homes (Table 3). Measures to specifically protect the elderly were relatively rare in mid-March, but have become more common across countries since then (see Table 4 for OECD countries).[4]

[4] These variables as well as the mask wearing variable are constructed using text search in three Covid-19-related databases: the COVID-19 Government Measures Dataset, run by the Assessment Capacities Project (ACAPS); a database on government responses to the coronavirus compiled by the CoronaNet Research Project; and the CCCSL dataset of the Complexity Science Hub Vienna. These record press and government statements with regard to public policy interventions to reduce the spread of Covid19, obtained from media, government communications and press releases from the United Nations and other international organisations. For every variable, a search is carried out for one or several keywords and the results are evaluated and coded. A potential shortcoming of this approach is that government policies not discussed publicly, or not communicated actively, might not appear in these datasets and hence might not be included in the analysis.

2.5. Mask-wearing

Evidence increasingly suggests that face masks can provide a potentially powerful protection against the transmission of SARS-CoV-2, which travels through droplets dispersed in the air (He et al., 2020, Lau et al 2020). This is especially true in closed and densely packed spaces and because a considerable share of infected people show no symptoms but have a high viral load. Meta-analysis of a large number of non-clinical trials of various coronaviruses indicates that mask wearing reduces significantly the infection rate, especially for masks of the N95 type (Chu et al. 2020; Schünemann et al., 2020), but even cloth masks are found to block infection (Mills et al. 2020). More direct evidence for SARS-CoV-2 comes from small-scale clinical trials, which confirm the desirability of mask wearing in public (Raina et al., 2020).[5]

Measuring the health-effects of mask-wearing at the regional or country-level, based on public policy pronouncements, is difficult because they might depend on the take-up rate and correct use (covering both mouth and nose) and it is difficult to account for the greater tendency to wear face masks, regardless of policy pronouncements, in some (mostly Asian) countries prior to the current virus outbreak. Nevertheless, recent studies provide empirical support for the beneficial effects of mask wearing. For instance, in a large cross-sectional dataset, public mask wearing was found to be negatively related to mortality (Leffler et al., 2020). Another country-level study sheds light on the negative correlation between mask wearing and infections for U.S. counties and two different cross-sectional datasets (Hatzius et al., 2020). Finally, Mitze et al. (2020) conclude that mask wearing successfully lowered infection rates in German regions adopting compulsory mask wearing policies. Countries have been mandating mask wearing more forcefully. While few countries had mandatory mask wearing in closed public spaces in mid-March, a majority of OECD countries had adopted such measures by end-July (Table 4).

In the current empirical framework, mask wearing is investigated using variables constructed by the authors, which denote whether there is an obligation to wear masks in shops, public transport or more generally in closed spaces (Table 3).

Table 3. Scoring of additional public health measures

Public health measure	Scoring of degree of stringency
Protection of the elderly	
Testing in care homes	1: Testing of residents and/or staff in care homes, regional level 2: Testing of residents and/or staff in care homes, national level
Restricting visits to care homes	1: Ban on visits, regional level 2: Ban on visits, national level
Keeping the elderly at home	1: Government recommendation to stay at home
Mask wearing	
Compulsory mask wearing indoors	1: Mandatory at the local level 2: Mandatory nationwide

Source: Constructed by the authors using text search in three Covid-19-related databases.
Source: Authors.

[5] There is also mounting anecdotal evidence in favour of mask wearing: a sick traveller wearing a mask not infecting fellow passengers; sick hairdressers not contaminating mask-wearing clients; and Starbucks employees in Korea wearing a mask not catching Covid-19 while customers were infected by a super-spreader individual (Bai, 2020).

2.6. Induced cautious behaviour and towards achieving herd immunity

In addition to the variables representing policy responses, the regression analysis also includes different measures of the death rate from the virus as explanatory variables.[6] Both the national and global daily death rates are included to proxy for general awareness of the virus prompting more cautious behaviour, for example voluntary physical distancing and increased hand-washing. The importance of these variables is that they proxy for changes in behaviour that are likely to be engendered regardless of government-mandated restrictions. In the case of the United States, for instance, Goolsbee and Syverson (2020) found that visits to businesses declined by up to 60% because of the pandemic, but that legal restrictions explained only 7 percentage points of this drop. Individual choices were far more important and seemed tied to fears of infection as differences in consumer traffic across counties were highly influenced by reported Covid-19 deaths.

Total national deaths attributed to the virus expressed as a share of the population are also separately included, as a proxy for the share of the population that has been infected, with the expectation of a negative coefficient; as the share of the population that has been infected rises (and presumably becomes immune), the speed with which the virus spreads will be reduced.

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[6] A possible concern with using death rates as proxies on the right-hand side of the equation is that the left-hand side variable (reproduction rate) is already partly estimated based on deaths. This potential problem is attenuated by differences in timing, however. While timing can only be addressed imperfectly because the raw data on deaths are smoothed, the idea is that the reproduction rate for day t is based on infections confirmed on day t+12 and on deaths recorded on day t+22. These leads are incorporated to account for average delays between infections and case detection, as well as average delays between infection and deaths, in the epidemiological literature (see Annex A). In any case, the coefficients on the policy variables of interest are reasonably robust to excluding the death variables from the R regression, although they increase to some extent.

Table 4. OECD countries scoring highly on specific policies

Month first implemented	Recommend elderly stay-at-home	Restrict visits to care homes	Test in care homes	Mandate mask wearing indoors
March	Czech Repubic	Austria	Norway	Switzerland
	Finland	Canada	Czech Republic	
	Hungary	Chile	Lithuania	
	Ireland	Czech Republic	Sweden	
	Mexico	Denmark	United States	
	Netherlands	Finland		
	Slovakia	Germany		
	Slovenia	Hungary		
	Spain	Israel		
	United States	Italy		
		Luxembourg		
		Netherlands		
		Portugal		
		Slovakia		
		United States		
April	Poland	Sweden	Austria	Canada
		Switzerland	Belgium	Chile
			Denmark	
			Ireland	
			Israel	
			Luxembourg	
			Portugal	
			Switzerland	
May	South Africa	Norway		Austria
		Turkey		Czech Republic
				Estonia
				Finland
				France
				Greece
				Israel
				Lithuania
				Portugal
				Slovakia
				Turkey
June				Japan
				Netherlands

Note: ‘Mask-wearing indoors’ denotes mandatory mask wearing in all closed public spaces.
Source: Variables constructed by the authors using text search in three Covid-19-related databases, see footnote 5.

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3. Empirical evidence on the impact of policies on the reproduction rate and mobility

This section describes the estimated effects of containment measures, testing policies, and other public health measures on both the reproduction rate, R (Table 5), and mobility (Table 6), which underlie the policy scenarios presented in the subsequent section.

3.1. The reproduction rate

The (exponential of the) constant in the equations shown in Table 5 can be used to infer an average initial reproduction rate, R0, which is relevant at the start of an epidemic and applies to a population previously free of infection and before any containment or other public health policies have been implemented. R0 is not purely a feature of the virus – it depends on the conditions in which the virus emerges, for instance in terms of population density, social norms, etc. R0 would thus be expected to vary across countries, which is captured in estimation through the inclusion of country fixed effects.[7]

An important feature of the estimated equation explaining R is that the preferred functional form for the dependent variable is logarithmic; a formal test decisively rejects a linear form in favour of a logarithmic one.[8] This implies that any policy intervention will have a larger effect when R is initially high than when it is low, and underlines the merit of early policy interventions.

3.1.1. Confinement policies

In estimation, the coefficients on five containment policies -- workplace closures, restrictions on gatherings, stay-at-home requirements, international travel controls and school closures -- are found to have a statistically significant effect in reducing R (Table 5). The coefficient on school closures has the largest effect of any containment policies, but there is a degree of collinearity between school closures, stay-at-home requirements and workplace closures arising because such containment policies have often been imposed at the same time.

Further testing suggests that while the sum of the coefficients on these three containment variables is a robust indication of the effect of a combined package, the coefficient on any one of them is less reliable as it is sensitive to the exclusion of other variables (and for this reason the combined effect of these three policies is summarised in Figure 5 and referred to as a 'Typical lockdown', rather than showing each of them individually). Similarly, the absence of any role for the closure of public events in the equation is likely related to its overlap with restrictions on the size

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[7] The estimated equation includes a full set of country fixed effects to account for fixed country characteristics that could affect virus transmission. There are many such factors, including population density, general social habits, climate, etc. One possibility would be to attempt to include these factors individually, but some factors (such as social habits) are difficult to quantify and failure to account for some important ones could result in omitted-variable bias. Some differences across countries which have been associated with variations in mortality from Covid-19 in the epidemiological literature, such as prevalence of certain conditions or diseases (obesity, diabetes, cardiovascular diseases, etc.), would not necessarily be expected to affect virus, transmission itself, which is the dependent variable here. At the same time, estimation of the reproduction number relies in part on death counts, and there could also be an indirect link between mortality and virus transmission, for instance if a lot of transmission happens in health settings where more serious cases end up. In any case, the country fixed effects would also absorb cross-country differences in determinants of mortality.

[8] Testing the appropriate functional form of the dependent variable is not as straightforward as testing for the functional form of explanatory variables because the competing models cannot be nested within a general model. The test is therefore conducted by first transforming the dependent variable by dividing by its geometric mean to make the two competing models (log and linear) comparable. A formal test of model equivalence can be performed with the BoxCox statistic by comparing the relative goodness-of-fit of the two models. The test decisively favours the logarithmic form for R over different country samples. Conversely, when a similar test is carried out for the mobility equation, the linear form is decisively preferred to the logarithmic form.

of gatherings, which is included. The combined effect of applying all containment polices suggests that from an initial R0 value of about 3, a complete package of containment measures would nearly halve the reproduction number.[9]

An interesting finding is that the impact differs substantially across countries: workplace closures have a considerably larger negative effect on R in high-income countries as compared to other countries.[10] One possible reason may be that workplace closures can be enforced more effectively in high-income countries while workers, more likely to be covered by social insurance, may be less tempted to circumvent them. This finding is mirrored in the mobility equation: workplace closures have a larger impact in advanced economies. Conversely, while stay-at-home requirements are found to reduce R to a greater extent in advanced economies than in less developed countries, this is not the case for mobility. The lower effectiveness of stay-at-home requirements in less advanced economies may be attributable to larger household sizes and smaller living spaces (Table B.3 in Annex B).

An important feature of these results is that the full R reduction is often achieved well before the maximum level of stringency is reached: for example a stringency score of 2 on the workplace closure variable reduces R, but it is not possible to detect any additional effect on R from a further increase in the degree of stringency. The combined effect of applying all containment polices suggests that from an initial R0 value of about 3, a complete package of containment measures would nearly halve the reproduction number (Figure 5).[11]

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[9] The OECD Economics Department compiled an alternative dataset of containment policies covering five areas: stay-at-home requirements, workplace closures, school closures, cancellation of public events and travel restrictions (Bulman and Koirala, 2020). While these indicators overlap with the Oxford measures, their definitions and coding differ. All policies are scored from 0 to 5, except cancelling of public events, which ranges from 0 to 3. Equations for R based on the OECD indicators include 74 countries and yield results broadly consistent with those based on the Oxford indicators: containment measures as a whole reduce R substantially, even though the impacts of specific containment policies differ from the Oxford-based results. The estimated effects of public health policies do not change as well as the finding that test and trace policies are very effective in a low-infection environment (Table B.1 in Annex B). The OECD trackers of containment policies were discontinued as of October 2020.

[10] The sample is divided into two groups of countries: those whose GDP per capita was greater than USD 25 500 in 2018 in Purchasing Power Parity terms, and countries with lower per capita income levels.

[11] Note that given the log specification of R the effectiveness of policies in terms of their absolute effect on R is non-linear and weakens at lower initial values of R. In addition, as described in the scenario analysis below, the effect on R from a full package of lockdown measures is likely to be enhanced by greater caution from the general population.

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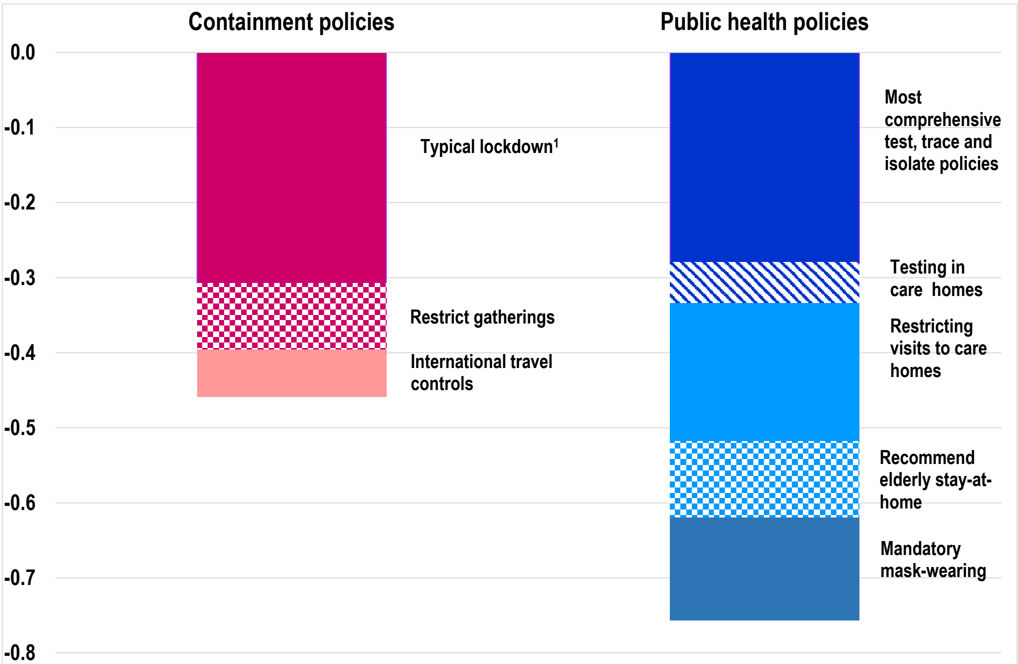
Figure 5. Effect of containment policies and public health policies on (logged) R



Note: This chart decomposes the effect on (logged) R from the different containment policies (left hand side red bars) and public health policies (right hand side blue bars) according to the regressions in Table 5.
(1)The effects of school closures (>=2), stay-at-home requirements (>=1) and workplace closures (>=2) have been combined into one segment labelled 'Typical lockdown'. This is both because such policies have often been imposed at the same time and, as discussed in the main text, because multi-collinearity means that the sum of the coefficients on these three containment variables are more reliable than any of the individual coefficients.
Source: Authors' calculations.

3.1.2. Test and trace policies

Results suggest that test and trace policies can reduce the spread of the virus (Table 5). The most comprehensive form of test and trace policies are more than 2½ times as effective in reducing R than more limited forms. Test and trace polices are most effective when the infection rate is not too high (which in estimation is taken to be less than 10 new daily cases per million population, a rate which was well exceeded by many countries in March and April), a rather unsurprising finding given the difficulties of tracking down all contact persons in a timely manner if the system is overwhelmed with new cases. Overall, the effect of the most effective test and trace regime in an environment of low daily infection, is estimated to have a greater effect on reducing R than any other public health interventions and is 2-3 times more effective than most individual containment measures (

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Figure 5). Variant regressions show that isolating the contacts of people who are sick or tested positive with the virus has a non-trivial effect on R and enhances substantially the effectiveness of test and trace policies (Table B.5 in Annex B).

3.1.3. Protecting the elderly

The empirical analysis provides strong evidence that policies can play an important role in shielding the elderly population. Stepping up the testing of residents and staff in long-term care facilities is found to correlate negatively with the transmission of the virus. Restricting visitor access to these establishments goes in tandem with lower reproduction rates. Furthermore, general stay-at-home recommendations for the elderly appears to be associated with less infections (Table 5). The combined effect of these polices on reducing R is estimated to exceed the effect of most individual containment measures, (

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Figure 5).

3.1.4. *Mask wearing*

Results show a sizeable and fairly robust negative effect on R from the introduction of mandatory mask wearing in all closed public spaces (Table 5), although other results (not reported) suggest that extending mask wearing obligations to the outdoors does not appear to add much to reducing the reproduction rate.

3.1.5. *Awareness of the virus and towards herd immunity*

The death rate variables are statistically significant with the expected negative sign and their magnitudes imply they can play an important role in the evolution of R.

The daily death rates are postulated to induce more cautionary behaviour. The global daily death rate has fluctuated around 0.5 per million during the period considered which, from an initial value of R0 of 3, would be expected to reduce R by about 0.6. The national daily death rate varies substantially, both across countries and over time, but for some OECD countries it was running at around 15 per million going into the lockdown in March, and this would reduce R by a further 0.6.

The total national death rate (i.e. based on cumulative deaths) also varies substantially across countries and has been increasing relentlessly through time in most countries. It is used here to proxy the profile of the number of people that have already been infected (and so are subsequently immune), so helping to reduce R. In a number of major OECD countries (including the United Kingdom, Spain, Italy and France) the total death rate currently exceeds 400 per million, at which level R would be reduced from 3 to 2.5.[12]

[12] The estimated coefficient on the total national death rate implies a herd-immunity threshold of about 1 600 deaths per million population (or 0.16%), since the estimated equation predicts that R would fall below one above this level of cumulative deaths. For an estimated average R0 of 3.0, a standard epidemiological relationship predicts herd immunity once (1 – 1 / 3) = 67% of the population has been infected (assuming persistent immunity). Both findings are consistent with current estimates of the infection fatality rate (IFR) for Covid-19, which is heavily stratified by age but ranges from 0.1% to 0.4% at the population level (Oke and Heneghan, 2020). Indeed, this IFR range corresponds to a population-fatality rate of 0.07% to 0.27% (= 67% * [0.1% to 0.4%]) for herd immunity. The estimated one (0.16%) falls within this range.

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Table 5. The drivers of the reproduction rate

Sample period: 1 January to 17 August 2020

Dependent variable: ln(R)	
Constant	1.0947**
Containment policies	
Stay-at-home requirement (>=1)	-0.0536**
Workplace closures (=1)	-0.0614**
Workplace closures (>=2)	-0.0767**
School closures (>=2)	-0.1773**
Restrictions on gatherings (=2)	-0.0393**
Restrictions on gatherings (>=3)	-0.0883**
International travel controls (>=1)	-0.0629**
Test and Trace policies	
Test=1 or 2, Trace =1 or 2	-0.1110**
Test=3, Trace=1	-0.1364**
Test=3, Trace=2	-0.2185**
All Test & Trace combinations when deaths < 10 per million	-0.0613**
Policies protecting the elderly	
Testing in care homes (=2)	-0.0540**
Restricting visits to care homes (>=1)	-0.1840**
Recommending elderly to stay at home	-0.1022**
Other non-containment policies	
Mandatory mask wearing indoors	-0.1370**
Death rates (per million population)	
Daily national	-0.0358**
Daily global	-0.3637**
Total national	-0.0007**
Adjusted R-squared	0.597
Daily observations	17624
Countries covered	147
Country fixed effects	Yes

Note: For details of the construction of data on R see Annex A. The policy variables are based on the variables described in Tables 1 to 3 in the main text, but re-normalised to be (0, 1) dummy variables as described in the main text. The notation in brackets "(=n)" after a containment policy variable denotes that the dummy variable is assigned a 1 if the original score for that policy was equal to n, whereas the notation "(>=n)" denotes that the dummy variable is assigned a 1 if the original score for that policy was greater than or equal to n. "**" denotes statistical significance at the 5% level, based on heteroscedasticity-robust standard errors.
Source: Authors' calculations.

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3.1.6. The policy drivers of mobility

Putting in place containment and isolation policies hinders the free daily movement of people. Empirical results[13] suggest that seven of the eight categories of containment policies have a negative effect on mobility (Table 6).[14] Unlike in the equation for R, there is a clearer ranking in coefficients, so that the more stringent application of a particular policy tends to reduce mobility by more. For example: the most severe form of workplace closure (score of 3) has nine times the effect on mobility of the mildest form (score of 1). These findings suggest that moving to the more stringent forms of workplace closure, stay-at-home requirements and school closure has large negative effects on mobility and hence economic activity, although it is difficult to detect any corresponding benefit from further reductions in R.[15]

For policies such as the cancellation of public events and travel restrictions, the most limited application of the policy has no significant effect on mobility. Applying all containment policies in their most severe forms would reduce mobility by more than half relative to normal, with 50% of this reduction accounted for by workplace closures and stay-at-home requirements.

Alternative estimations explore the effect of mask-wearing on mobility. The positive coefficient estimates suggest that mandating mask wearing in public transports and shops raises mobility. Similarly, more extensive testing and the isolation of contact persons are found to encourage mobility (Table B.6 in Annex B), possibly by reducing concerns about infection.

The national daily death rate from the virus is again included to proxy general awareness of the virus and its effect in voluntarily reducing mobility due to an increase in natural caution. A national daily death rate running at around 15 per million – similar to the rate experienced by some major OECD countries going into the lockdown in March – would reduce mobility by 10%, independently of any government-mandated polices.

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[13] For the estimated equation explaining mobility, unlike that for R, the preferred functional form for the dependent variable is linear, not logarithmic, which makes it more straightforward to evaluate the effect of policies. The specification includes a full set of country fixed effects to account for invariant country characteristics, although their inclusion is much less critical here given that mobility is a relative measure constructed so that it equals one in normal times in each country.

[14] The failure to detect any effect from restrictions on gatherings is likely related to its close correlation with the policy to cancel public events.

[15] Using the OECD containment measures (covering 68 countries) yields very similar estimation results (Table B.2 in Annex B).

Table 6. The drivers of mobility

Sample period: 1 January to 17 August 2020

Dependent variable: Mobility	
Constant	1.0241**
Containment policies	
Stay-at-home requirement (=1)	-0.0240**
Stay-at-home requirement (=2)	-0.0668**
Stay-at-home requirement (=3)	-0.1252**
Workplace closures (=1)	-0.0216**
Workplace closures (=2)	-0.0491**
Workplace closures (=3)	-0.1980**
School closures (=2)	-0.0237**
School closures (=3)	-0.1098**
Cancel public events (=2)	-0.0369**
Restrictions on internal movement (=2)	-0.0220**
International travel controls (=4)	-0.0554**
Close public transport (=1)	-0.0439**
Close public transport (=2)	-0.0650**
Death rate (per million population)	
Daily national	-0.0066**
Adjusted R-squared	0.759
Daily observations	22741
Countries covered	128
Country fixed effects	Yes

Note: Mobility data are made available by Google, based on the movement of people with 'location history' turned on in their smartphone settings. The index used here measure the change in mobility from a same-day-of-the-week average in January and early February, so that normality would suggest an index of 1.0. The containment policy variables are based on those summarised in Table 1, but re-normalised to be (0, 1) dummy variables as described in the main text. The notation in brackets "(=n)" after a containment policy variable denotes that the dummy variable is assigned a 1 if the original score for that policy was equal to n, whereas the notation "(>=n)" denotes that the dummy variable is assigned a 1 if the original score for that policy was greater than or equal to n. "**" denotes statistical significance at the 5% level.
Source: Authors' calculations.

4. Scenario analysis

As reported in the previous section, equations estimated for a large sample of countries find well-determined effects from containment policies on R and mobility, as well as strongly significant effects from a range of health policies on R. However, another important feature of both equations is that the prevalence of the virus is found to alter behaviour regardless of government-mandated policies: mobility is reduced and the general population is more ready to adopt physical distancing and other measures which reduce R. In order to draw out the policy implications of these estimations, a number of stylised scenarios are constructed using the estimated equations to follow the evolution of R and mobility from the first outbreak of the virus, through full lockdown, followed by a number of alternative exit strategies (Figure 6, Table 7).

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At the first outbreak of the virus, for the typical country, the initial reproduction number R0 is estimated to be about 3 and, before the impact of the virus is felt on the economy, mobility is normal (represented by the red triangle at the top right-hand-side corner of Figure 6). Even before the implementation of government-mandated measures, awareness of the seriousness of the virus (represented by the daily death rate) is likely to reduce mobility and foster more cautious behaviour, leading to a fall in R, although it remains well above 1.0 (the red triangle-labelled "*Pre-lockdown + natural caution*" in Figure 6, which is calibrated on the daily death rates of a number of major OECD economies just prior to lockdown).

Once the number of daily infections is high (here proxied by the high national daily death rate), the implementation of a wide range of containment measures will be essential to contain the spread of the virus. In the scenarios considered here, the implementation of full lockdown (FLD) measures, accompanied by a limited test-and-trace regime, reduces R to close to 1.0, but at the cost of a sharp fall in mobility (represented by the blue squares in Figure 6). The degree of stringency with which lockdown measures are applied will determine the extent of the fall in mobility, with two scenarios considered here: the first assumes that containment policies are applied with a degree of stringency which is typical of that followed by countries in March/April (corresponding to the median country); the second assumes all containment policies to be applied to their maximum possible degree of stringency. Mobility falls by more than 40% in the former case and by more than 60% in the latter, however the estimation results suggest there is little additional benefit in terms of lowering R from maximising the degree of stringency of containment policies (particularly with regard to workplace closures or stay-at-home requirements).

Even in the absence of further policy changes, the reproduction number will evolve during lockdown as the number of infections/deaths change the fall in the daily death rate may tend to lower natural caution and so lead to some increase in R and mobility; on the other hand, as the total number of individuals that have already been infected and are immune rises then this will tend to lower R. The estimation results and particular calibrations used in constructing these scenarios suggest these two effects roughly cancel each other out.

A number of strategies for avoiding a full lockdown are considered (represented by the green circles in Figure 6). The basic issue facing policy-makers is how to prevent the need for the full set of containment policies while bringing or keeping R under control. The estimation results (Table 5) suggest that the implementation of a comprehensive test and trace policy together with a package of other public health measures would more than compensate for the removal of lockdown policies, so that their successful implementation would see a return to near normality of mobility, with R remaining below 1 (as represented by the green circle labelled "*No LD + full health measures*" in Figure 6).

An even more decisive reduction in R below 1 might be achieved, if comprehensive public health measures were accompanied by maintaining some containment policies (here assuming that restrictions on large public events, large public gatherings and international travel remain), although it would come at some cost to mobility (*Partial LD + full health measures*" in Figure 6).

In practice, as the experience of several countries is showing, implementing a full range of public health policies and a comprehensive test and trace regime may be difficult, especially once the daily infection rate has begun to rise. Variant scenarios with "*limited health measures*" assume only a limited test-and-trace regime together with mandating mask-wearing in indoor public places, but no other public health policies targeted at the elderly or care homes. Such a combination of policies accompanied by a full relaxation of lockdown measures might see mobility initially return to just below normal levels (assuming the daily death rate has previously been reduced by lockdown), but R will likely increase well above 1.0 (represented by the scenario labelled "*No LD + limited health measures*" in Figure 6). However, this situation would not be a stable equilibrium, as with R above 1.0 there would be a subsequent pick-up in infections and deaths, which in turn would further reduce mobility, regardless of further government action.

A limited set of health measures accompanied by maintaining the same limited containment policies, would come at a more immediate cost to mobility, but bring R down by more, although in the scenario considered here it would still remain above 1 ("*Partial LD + limited health measures*"), and so would not represent a sustainable situation.

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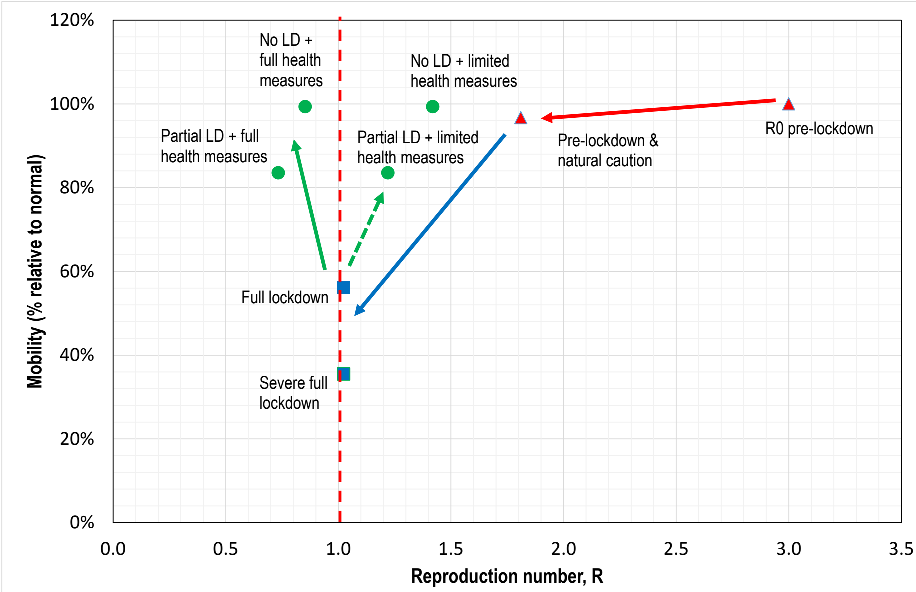
Figure 6. Stylised scenarios: from the first outbreak of the virus, through lockdown and exit



Note: The points represent scenarios, each of which are generated from consistent combinations of the equations for R and mobility using assumptions for the explanatory variables that are summarised in Table 7. The red triangles denote the situation at the start of the virus outbreak, blue squares the situation following full lock-down policies, and the green circles represent various exit scenarios.

Source: Authors.

Table 7. Scenario assumptions and outcomes for R and mobility

Scenario	Containment measures	Testing,tracing & isolation		Other public health policies				Daily national deaths	Daily global deaths	Total national deaths	R	Mobility index (1.00 = normal)
		Extensive	Limited	Mask-wearing	Testing in care homes	Elderly stay at home	Ban care home visits	per million of population				
Pre-lockdown												
R0	None	-	-	-	-	-	-	0	0	0	3.00	1.00
Natural caution	None	-	-	-	-	-	-	5.0	0.8	50	1.81	0.97
Lockdown												
Full lockdown (FLD)	Comprehensive	-	√	-	-	-	-	5.0	0.8	50	1.02	0.56
Severe FLD	Comprehensive & severe	-	√	-	-	-	-	5.0	0.8	50	1.02	0.35
Exit from lockdown												
Partial LD & full health measures	Ban large public events, restrict gatherings, quarantine international travellers	√	-	√	√	√	√	1.0	0.7	300	0.73	0.84
Partial LD & limited health measures	Ban large public events, restrict gatherings, quarantine international travellers	-	√	√	-	-	-	1.0	0.7	300	1.22	0.84
No LD & full health measures	None	√	-	√	√	√	√	1.0	0.7	300	0.85	0.99
No LD & limited health measures	None	-	√	√	-	-	-	1.0	0.7	300	1.42	0.99

Note: The assumptions here correspond to the scenarios illustrated in Figure 6.
Source: Authors' calculations.

4.1. Which lockdown policies should stay in place longest?

The policy scenarios suggest that a prudent strategy would likely consist of imposing some lockdown policies, at least until it is clear that R remains decisively below 1. This raises the question as to whether the estimations help to inform this choice by suggesting policies with a better trade-off in terms of the benefit from virus control relative to the cost in terms of mobility foregone. There are, however, some reasons for caution in interpreting the results in this way. Firstly, as previously noted, there is evidence of collinearity between some containment policies -- notably school closures, workplace closures and stay-at-home requirements -- which suggests particular caution in interpreting the estimated coefficients relating to these policies. Secondly, while most containment policies have, at some level of stringency, an effect on R and mobility which is statistically significantly different from zero, the difference between policies, particularly as regards the effect on R, is often not statistically significant.

Bearing these limitations in mind, the containment policies which appear the most obvious candidates for extension are:

- Restrictions on international travel, including obligations to quarantine all arrivals from selected countries, would reduce R significantly and may have only a small effect on mobility (although this may be because the mobility measure does not capture international mobility accurately).
- Restrictions on gatherings has a substantial effect on reducing R, whereas the cancellation of public events (which would seem to be inevitably linked) has a relatively small effect on mobility. Such policies may be particularly effective because such large public gatherings may otherwise represent a risk of being so-called '*superspreader*' events.

In both cases, such measures might have serious adverse effects on particular sectors of the economy (notably, entertainment and travel) which might warrant some targeted support. However, their effect on wider economic activity may be more limited than that of other containment measures.

The estimation results also suggest that resort to the most stringent form of workplace closures, school closures and stay-at home requirements at the national level are likely to have a relatively large adverse effect on mobility (and by extension economic activity) relative to the reduction in R achieved.

5. Conclusion

Recent optimistic news about the availability of a number of vaccines against the coronavirus needs to be tempered by the realisation that, even in the countries that are in the vanguard, it is likely to be the middle of next year before a large share of the population has been vaccinated. In the meantime, governments around the world will be trying to calibrate policy interventions so as to keep the spread of the disease under control without crippling economic activity.

This study uses country experience during the first phase of the pandemic to estimate the impact of different government interventions on both the reproduction rate of the virus, R, and on mobility, as a proxy for economic activity. The empirical results then inform a number of scenarios where the epidemic/economic trade-off of different policy packages is assessed:

- When the daily infection rate is high, a comprehensive combination of containment policies is needed to reduce the spread of the virus, although these are likely to severely reduce mobility and economic activity.
- Once the daily infection rate has been lowered, test-and-trace policies represent a better alternative for controlling the virus, because they have no significant adverse impact on mobility or economic activity. Testing is found to be more effective in reducing R if accompanied by comprehensive contact tracing. Specific testing in care homes is also important to control the spread of the virus.

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- Other public health policies can also contribute to restraining the spread of the virus, including: mandating mask-wearing in public indoor environments; restricting visits to care homes; and stay-at-home recommendations for the elderly population.

Even with a comprehensive test-and-trace regime and supporting public health policies, there may be a need to resort to selective containment measures. These should prioritise restrictions on large gatherings and international travel. Where there are localised outbreaks of the virus, then targeted lockdown measures are appropriate.

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Annex A. Estimation of effective reproduction number (R)

The estimation of effective reproduction numbers relies on code developed by Systrom (2020), who extends the static Bayesian approach of Bettencourt and Ribeiro (2008) to estimate a time-varying R_t for US states. The code is adapted slightly to apply it to countries instead of US states and to combine information from both confirmed cases and deaths.

The basic idea is to estimate R_t as a function of how many new cases appear each day using Bayes' Theorem. New information from each day's case count is used to adjust expectations of what R_t is, getting closer to the true value as more daily data become available.

Formally, the likelihood that the reproduction rate is R_t given k_t new cases on day t, $P(R_t|k_t)$, is:

$$P(R_t|k_t) = \frac{P(k_t|R_t) \cdot P(R_t)}{P(k_t)} \quad [1]$$

where $P(k_t|R_t)$ is the likelihood of seeing k_t new cases on a given day given R_t, $P(R_t)$ is the prior belief about the value of R_t without today's data and $P(k_t)$ is the probability of seeing this many cases in general. Obtaining the likelihood function $P(k_t|R_t)$ starts from the Poisson distribution for the probability of seeing k_t new cases given an average arrival rate of new cases per day (λ).

$$P(k_t|\lambda) = \frac{\lambda^{k_t} e^{-\lambda}}{k_t!} \quad [2]$$

The average arrival rate of new cases (λ) relates to the effective reproduction number of an infectious disease in the following manner [see Bettencourt and Ribeiro (2008) for the derivation]:

$$\lambda = k_{t-1} e^{\gamma(R_t - 1)} \quad [3]$$

where γ is the reciprocal of the serial interval (i.e. the average number of days over which an infected person will contaminate others). Based on the epidemiological literature, a serial interval of seven days is assumed here (Anderson et al., 2020 and Salje et al., 2020). Given this assumption and an observation for cases on the previous day (k_{t-1}), equation [3] can be substituted into equation [2] to obtain $P(k_t|R_t)$.

Except for the first day, where an independent prior is needed, the prior probability in equation [1], $P(R_t)$, is based on yesterday's posterior estimate, $P(R_{t-1})$. The distribution of R_t is assumed to be a Gaussian centred on R_{t-1}, so $P(R_t|R_{t-1}) = \mathcal{N}(R_{t-1}, \sigma)$, where σ is a Gaussian noise parameter reflecting the belief that the value of R_t likely changes from day to day. The higher σ, the more noise and the more the value of R_t is expected to drift each day. Applying noise on noise iteratively means that there is a natural decay of distant posteriors.

The denominator of Bayes' rule in equation [1] is given by:

$$P(k_t) = \sum_{R_t} P(k_t|R_t) \cdot P(R_t) \quad [4]$$

It is the sum of the distribution of the numerator over all possible values of R_t (assumed to theoretically range from 0 to 12). The value of σ is chosen so as to maximise the likelihood of the observed data over all days t and countries i, $P(k)$:

$$P(k) = \prod_{i,t} P(k_{i,t}) \qquad [5]$$

The procedure just described is applied separately to the worldwide daily dataset of new cases and new deaths. The idea is that both series contain some information about the progression of the epidemic and a better estimate can likely be obtained by combining this information. The series for daily new cases and new deaths are sourced from the European Centre for Disease Prevention and Control (ECDC). To reduce noise, the raw series are filtered using a 7-day centred rolling Gaussian window before estimation.

Nationally reported statistics on Covid-19 cases and deaths can be affected by measurement errors, while differences in coding and reporting practices pose challenges when used for international comparisons. A possible alternative would be to look at all-cause (excess) mortality, which takes into account the possible underreporting of Covid-19 deaths (OECD, 2020b). However, this measure would reflect indirect effects, possibly positive (e.g. fewer road fatalities) or negative (e.g. increased mortality caused by foregone treatment).

As this study focuses on dynamics of the epidemic per se, excess mortality has not been considered as a convenient outcome variable. In addition, use of excess mortality would severely limit the estimation sample. Measures of excess deaths are currently available for only about 25 countries and only at the weekly or monthly frequency. For some countries, the data cover only selected major cities. Timeliness is another issue, in some countries the data are only made available with a lag of several weeks or even months. Working with the available excess deaths data at the weekly frequency would therefore mean shrinking the sample coverage substantially in both the country and time dimensions. Finally, to the extent that new infections have skewed toward younger age groups over the Northern Hemisphere summer, as reported by many countries, excess deaths may no longer be an accurate reflection of the number of new infections. The same issue applies to R measures based on deaths. This is one reason why the R measure used in the main analysis is an average of two R independent estimates, one based on new cases and one based on new deaths.

When both the case-based and death-based R_t can be calculated for a given country and day, the final R_t estimate is an average of the two, except that a 10-day lead is applied to the death estimate to reflect the time window between case detection and death, consistent with Anderson et al. (2020) and Salje et al. (2020). The average time lag between infection and case detection is taken into account in the regression model itself by leading the R_t series as dependent variable by 12 days relative to the right-hand side variables (e.g. government interventions). This means that the regressions assume an average of 12 days between infection and case confirmation, and 22 days (12 days + 10-day lead for deaths) between infection and death. For some countries and time periods where deaths are too low to calculate a death-based R_t, only the case-based estimate can be computed. In such cases, the final R_t estimate is based on new cases only. This is also true of the most recent ten days of the sample period given the lead applied to the deaths estimate.

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Annex B. Auxiliary regression results

Table B.1. The drivers of the reproduction rate, OECD containment measures

	Oxford indicators Baseline regression from Table 5		**OECD indicator**
Dependent variable: ln(R)			
Constant	1.0947**	Constant	0.9441**
Containment policies			
Stay-at-home requirement (>=1)	-0.0536**	Stay-at-home requirement (=1)	-0.0257**
		Stay-at-home requirement (>=2)	-0.1083**
Workplace closures (=1)	-0.0614**	Workplace closures (>=1)	-0.0263**
Workplace closures (>=2)	-0.0767**		
School closures (>=2)	-0.1773**	School closures (>=2)	-0.1346**
Restrictions on gatherings (=2)	-0.0393**	Restrictions on gatherings (>=2)	-0.2167**
Restrictions on gatherings (>=3)	-0.0883**		
International travel controls (>=1)	-0.0629**		
Test and Trace policies			
Test=1 or 2, Trace =1 or 2	-0.1110**		
Test=3, Trace=1	-0.1364**		
Test=3, Trace=2	-0.2185**		
All Test & Trace combinations when deaths < 10 per million	-0.0613**		-0.1279**
Policies protecting the elderly			
Testing in care homes (=2)	-0.0540**	Testing in care homes (=2)	-0.0267*
Restricting visits to care homes (>=1)	-0.1840**	Restricting visits to care homes (>=1)	-0.1146**
Recommending elderly to stay at home	-0.1022**	Recommending elderly to stay at home	-0.1451**
Other non-containment policies			
Mandatory mask wearing indoors	-0.1370**	Mandatory mask wearing indoors	-0.1047**
Death rates (per million population)			
Daily national	-0.0358**	Daily national	-0.0295**
Daily global	-0.3637**	Daily global	-0.3732**
Total national	-0.0007**	Total national	-0.0006**
Adjusted R-squared	0.597		0.642
Daily observations	17624		8984
Countries covered	147		74
Country fixed effects	Yes		Yes

Note: As for Table 5.
Source: Authors' calculations.

Table B.2. The drivers of mobility, OECD containment measures

Sample period: 1 January to 17 August 2020

	Oxford indicators Baseline regression from Table 6	**OECD indicators**
Dependent variable: Mobility		
Constant	1.0241**	0.9454**
Containment policies		
Stay-at-home requirement (=1)	-0.0240**	-0.0165**
Stay-at-home requirement (=2)	-0.0668**	-0.0406**
Stay-at-home requirement (=3)	-0.1252**	-0.0749**
Stay-at-home requirement (=4)		-0.0777**
Stay-at-home requirement (=5)		-0.1733**
Workplace closures (=1)	-0.0216**	0.0117**
Workplace closures (=2)	-0.0491**	-0.0404**
Workplace closures (=3)	-0.1980**	-0.0531**
Workplace closures (>=4)		-0.1120**
School closures (=2)	-0.0237**	-0.0744**
School closures (=3)	-0.1098**	-0.1413**
School closures (=4)		-0.1450**
School closures (=5)		-0.2188**
Cancel public events (=2)	-0.0369**	
Cancel public events (=3)		-0.0562**
Restrictions on internal movement (=2)	-0.0220**	
International travel controls (=4)	-0.0554**	
Close public transport (=1)	-0.0439**	
Close public transport (=2)	-0.0650**	
Death rate (per million population)		
Daily national	-0.0066**	-0.0092**
Adjusted R-squared	0.759	0.633
Daily observations	22741	12122
Countries covered	128	68
Country fixed effects	Yes	Yes

Note: As for Table 6
Source: Authors' calculations.

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Table B.3. The drivers of the reproduction rate, advanced vs. emerging and developing countries

Sample period: 1 January to 17 August 2020

	Baseline, Table 5	Variant 1	Variant 2
Dependent variable: ln(R)			
Constant	1.0947**	1.0361**	1.0312**
Containment policies			
Stay-at-home requirement (>=1)	-0.0536**	-0.0570**	-0.0150*
Stay-at-home requirement (>=1) in advanced economies			**-0.1182****
Workplace closures (=1)	-0.0614**	0.0249*	0.0122
Workplace closures (=1) in advanced economies		**-0.2134****	**-0.1765****
Workplace closures (>=2)	-0.0767**	0.0125	-0.0104
Workplace closures (>=2) in advanced economies		**-0.2474****	**-0.1762****
School closures (>=2)	-0.1773**	-0.1636**	-0.1580**
Restrictions on gatherings (=2)	-0.0393**	-0.0463**	-0.0461**
Restrictions on gatherings (>=3)	-0.0883**	-0.0809**	-0.0803**
International travel controls (>=1)	-0.0629**	-0.0447**	-0.0527**
Test and Trace policies			
Test=1 or 2, Trace =1 or 2	-0.1110**	-0.1248**	-0.1233**
Test=3, Trace=1	-0.1364**	-0.1281**	-0.1240**
Test=3, Trace=2	-0.2185**	-0.2330**	-0.2317**
All Test & Trace combinations when deaths < 10 per million	-0.0613**	-0.0552**	-0.0550**
Policies protecting the elderly			
Testing in care homes (=2)	-0.0540**	-0.0390**	-0.0438**
Restricting visits to care homes (>=1)	-0.1840**	-0.1402**	-0.1324**
Recommending elderly to stay at home	-0.1022**	-0.0906**	-0.0893**
Other non-containment policies			
Mandatory mask wearing indoors	-0.1370**	-0.1501**	-0.1494**
Death rates (per million population)			
Daily national	-0.0358**	-0.0338**	-0.0329**
Daily global	-0.3637**	-0.3669**	-0.3749**
Total national	-0.0007**	-0.0006**	-0.0006**
Adjusted R-squared	0.597	0.598	0.6
Daily observations	17624	17624	17624
Countries covered	147	147	147
Country fixed effects	Yes	Yes	Yes

Note: As for Table 5.
Source: Authors' calculations.

Table B.4. The drivers of mobility, advanced vs emerging and developing countries

Sample period: 1 January to 17 August 2020

	Baseline, Table 6	Variant 1	Variant 2
Dependent variable: Mobility			
Constant	1.0241**	1.0237**	1.0236**
Containment policies			
Stay-at-home requirement (=1)	-0.0240**	-0.0228**	-0.0207**
Stay-at-home requirement (=2)	-0.0668**	-0.0668**	-0.0664**
Stay-at-home requirement (=3)	-0.1252**	-0.1265**	-0.1257**
Stay-at-home requirement (>=1) in advanced economies			**-0.0060**
Workplace closures (=1)	-0.0216**	-0.0233**	-0.0239**
Workplace closures (=2)	-0.0491**	-0.0416**	-0.042**
Workplace closures (=3)	-0.1980**	-0.1896**	-0.1903**
Workplace closures (=1) in advanced economies		**-0.0021**	**-0.0001**
Workplace closures (>=2) in advanced economies		**-0.0306****	**-0.0286****
School closures (=2)	-0.0237**	-0.0217**	-0.0217**
School closures (=3)	-0.1098**	-0.1085**	-0.1086**
Cancel public events (=2)	-0.0369**	-0.0358**	-0.0358**
Restrictions on internal movement (=2)	-0.0220**	-0.0226**	-0.0229**
International travel controls (=4)	-0.0554**	-0.0572**	-0.0571**
Close public transport (=1)	-0.0439**	-0.0443**	-0.0443**
Close public transport (=2)	-0.0650**	-0.0688**	-0.0684**
Death rate (per million population)			
Daily national	-0.0066**	-0.0060**	-0.0061**
Adjusted R-squared	0.759	0.759	0.759
Daily observations	22741	22741	22741
Countries covered	128	128	128
Country fixed effects	Yes	Yes	Yes

Note: As for Table 6.
Source: Authors' calculations.

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Table B.5. The drivers of reproduction rate, isolating contact persons

Sample period: 1 January to 17 August 2020

	Baseline, Table 5	Variant 1	Variant 2	Variant 3
Dependent variable: ln(R)				
Constant	1.0947**	1.0553**	1.0545**	1.0447**
Containment policies				
Stay-at-home requirement (>=1)	-0.0536**	-0.0501**	-0.0506**	-0.0486**
Workplace closures (=1)	-0.0614**	-0.0668**	-0.0677**	-0.0767**
Workplace closures (>=2)	-0.0767**	-0.0736**	-0.0742**	-0.0778**
School closures (>=2)	-0.1773**	-0.1615**	-0.1615**	-0.1615**
Restrictions on gatherings (=2)	-0.0393**	-0.0397**	-0.0404**	-0.0448**
Restrictions on gatherings (>=3)	-0.0883**	-0.0844**	-0.0849**	-0.0860**
International travel controls (>=1)	-0.0629**	-0.0439**	-0.0432**	-0.0430**
Test and Trace policies				
Test=1 or 2, Trace =1 or 2	-0.1110**	-0.0768**	-0.0778**	-0.0855**
Test=3, Trace=1	-0.1364**	-0.1015**	-0.1034**	-0.0998**
Test=3, Trace=2	-0.2185**	-0.1778**	-0.1800**	-0.1806**
All Test & Trace combinations when deaths < 10 per million	-0.0613**	-0.0608**	-0.0608**	-0.0243**
Isolating contact persons		**-0.2015****	**-0.2093****	**-0.1442****
Isolating the sick		**-0.0186****		
All Test & Trace combinations with isolation of contact persons when deaths < 10 per million				**-0.1338****
Policies protecting the elderly				
Testing in care homes (=2)	-0.0540**	-0.0588**	-0.0558**	-0.0543**
Restricting visits to care homes (>=1)	-0.1840**	-0.1869**	-0.1884**	-0.1865**
Recommending elderly to stay at home	-0.1022**	-0.1010**	-0.1025**	-0.1022**
Other non-containment policies				
Mandatory mask wearing indoors	-0.1370**	-0.1133**	-0.1131**	-0.1103**
Death rates (per million population)				
Daily national	-0.0358**	-0.0379**	-0.0378**	-0.0374**
Daily global	-0.3637**	-0.3358**	-0.3373**	-0.3385**
Total national	-0.0007**	-0.0007**	-0.0007**	-0.0007**
Adjusted R-squared	0.597	0.599	0.599	0.603
Daily observations	17624	17624	17624	17624
Countries covered	147	147	147	147
Country fixed effects	Yes	Yes	Yes	Yes

Note: As for Table 5.
Source: Authors' calculations.

Table B.6. The drivers of mobility: testing, isolating and mask wearing

Sample period: 1 January to 17 August 2020

	Baseline, Table 6	Test & trace & Isolate		Mask wearing	
Dependent variable: Mobility					
Constant	1.0241**	1.0214**	1.0075**	1.0184**	1.0177**
Containment policies					
Stay-at-home requirement (=1)	-0.0240**	-0.0239**	-0.0267**	-0.0264**	-0.0322**
Stay-at-home requirement (=2)	-0.0668**	-0.0659**	-0.0688**	-0.0665**	-0.0785**
Stay-at-home requirement (=3)	-0.1252**	-0.1258**	-0.1308**	-0.1301**	-0.1329**
Workplace closures (=1)	-0.0216**	-0.0207**	-0.0327**	-0.034**	-0.0342**
Workplace closures (=2)	-0.0491**	-0.0506**	-0.0604**	-0.0587**	-0.062**
Workplace closures (=3)	-0.1980**	-0.1972**	-0.2019**	-0.2009**	-0.1986**
School closures (=2)	-0.0237**	-0.0261**	-0.0315**	-0.0247**	-0.0333**
School closures (=3)	-0.1098**	-0.1116**	-0.1104**	-0.0992**	-0.1025**
Cancel public events (=2)	-0.0369**	-0.0379**	-0.0410**	-0.0397**	-0.0397**
Restrictions on internal movement (=2)	-0.0220**	-0.0215**	-0.0180**	-0.0215**	-0.0222**
International travel controls (=4)	-0.0554**	-0.0554**	-0.0576**	-0.0537**	-0.0504**
Close public transport (=1)	-0.0439**	-0.0469**	-0.0511**	-0.0496**	-0.0441**
Close public transport (=2)	-0.0650**	-0.0655**	-0.0703**	-0.0646**	-0.0632**
Isolating contact persons		**0.0322****	**0.0221****		
Test=1 or 2, Trace =1 or 2			**0.0276****		
Test=3, Trace=1			**0.0430****		
Test=3, Trace=2			**0.0732****		
Mandatory mask wearing indoors				**0.0605****	
Mandatory mask wearing in public transports					**0.0592****
Mandatory mask wearing in shops					**0.0644****
Death rate (per million population)					
Daily national	-0.0066**	-0.0066**	-0.0066**	-0.0071**	-0.0060**
Adjusted R-squared	0.759	0.758	0.763	0.762	0.766
Daily observations	22741	22383	22190	22383	22249
Countries covered	128	126	126	126	125
Country fixed effects	Yes	Yes	Yes	Yes	Yes

Note: As for Table 6.
Source: Authors' calculations.

Mobility under the COVID-19 pandemic: Asymmetric effects across gender and age[1]

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Overall mobility declined during the COVID-19 pandemic because of government lockdowns and voluntary social distancing. Yet, aggregate data mask important heterogeneous effects across segments of the population. Using unique mobility indicators based on anonymized and aggregate data provided by Vodafone for Italy, Portugal, and Spain, we find that lockdowns had a larger impact on the mobility of women and younger cohorts. Younger people also experienced a sharper drop in mobility in response to rising COVID-19 infections. Our findings, which are consistent across estimation methods and robust to a variety of tests, warn about a possible widening of gender and inter-generational inequality.

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1 The views expressed in this working paper are those of the authors and do not necessarily represent those of the IMF, its Executive Board, or its management. Working papers describe research in progress by the authors and are published to elicit comments and to encourage debate. We thank Pedro Rente LoureÇo and Vodafone's Big Data and Artificial Intelligence team for constructing the mobility indicators used in this study.
2 IMF.
3 IMF and CEPR.

CEPR PRESS

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1 Introduction

The COVID-19 pandemic dramatically reduced people's mobility. This was due in part to the lockdown measures that governments adopted to reduce personal contacts, including travel restrictions, school and business closures, and stay-at-home orders. Mobility also declined because people voluntarily reduced social interactions out of fear of contracting the virus. The literature has documented these effects using a broad range of *aggregate* mobility indicators provided by private companies such as Google, Apple, and SafeGraph (Chetty et al., 2020; Glaeser et al., 2020; Goolsbee and Syverson, 2020; Maloney and Taskin, 2020).

This paper innovates relatively to the existing studies by showing that mobility patterns differed considerably across gender and age groups. Our analysis is based on novel and confidential mobility indicators provided by Vodafone for Italy, Portugal, and Spain at the provincial level. These data offer the unique advantage of disaggregating mobility information across gender and age groups, making it possible to uncover important heterogeneous reactions to the pandemic and lockdown measures. This paper makes several contributions.

First, the analysis contributes to the growing evidence about the disproportionate impact of the COVID-19 crisis on women. This literature finds that some home production that in normal times can be outsourced had to be performed within the household during the pandemic. And this burden fell disproportionately on women. Hupkau and Petrangolo (2020), for example, find that in UK households women took on a larger share of increased childcare needs, even though fathers became the primary childcare providers in an important share of households. Alon et al. (2020) show that, contrary to past recessions, the current crisis led to a stronger increase in female unemployment in the US. This is because women are more likely to care for children when schools are closed and because they are employed in sectors more severely hit by the pandemic, such as restaurants and personal care. Survey data also suggest that women face an unequal burden in caring for children when schools are closed and are at a higher risk of facing a reduction in working hours (Adams et al., 2020; Sevilla and Smith, 2020). In this paper we document that the disproportional impact of the crisis on women is also visible in mobility patterns and examine the causes of this differential.

In this regard, this paper also contributes to the literature on the determinants of labor force participation. School closures and other lockdown measures reduce mobility in different ways across gender and thus have a differential effect on labor supply. Previous studies have found that exogenous changes in the length of school schedule impact female labor force participation (Berthelon et al., 2015). We provide high-frequency, complementary evidence.

Second, this paper documents considerable heterogeneity in the impact of lockdowns across age groups. These findings are quite relevant for the ongoing debate on the distribution of costs and benefits across generations (Belot et al., 2020; Glover et al., 2020). While lockdowns protect mainly older people that are more likely to develop serious medical conditions from COVID-19, they impose economic costs especially on working age people that rely on labor income to support consumption.

Third, the heterogeneous impact of lockdowns across age can shed light on the scarring effects from the crisis. For instance, a given reduction in aggregate mobility has different long-term effects if it is concentrated on the young. Oreopoulos et al. (2012) find that individuals entering the labor force during a recession suffer from substantial and persistent loss of earning; they also document that graduates who can switch quickly to better firms suffer less. So a forced reduction in mobility has a particularly adverse and persistent effect if it reduces the mobility of young.

Fourth, heterogeneous effects across gender and age raise important methodological considerations. Lumping all groups together in estimating the effects of containment measures as done in most studies could lead to aggregation bias and mismeasurement problems.

Fifth, in presence of repeated infection waves in several countries (as we write, many countries are experiencing a strong resurgence) and in the context of an already weak economic activity, authorities need to consider more nuanced containment measures. To design these measures, authorities should consider the heterogeneous effects on different groups. This perspective is particularly important because the health risks posed by COVID-19 are very heterogeneous across age, being much more severe for people aged 65 and above. Therefore, some researches have argued for targeted measures to isolate older people without unduly limiting the mobility and employment opportunities of younger people (Acemoglu et al., 2020).

Studying the effect of containment measures on mobility is a difficult task because the adoption of lockdowns is an endogenous policy decision. For example, governments are more likely to impose measures when health risks are more acute. At that time people tend to also reduce mobility voluntarily because they fear being infected or infecting others. This raises the risk of detecting a spurious correlation between lockdowns and mobility. To address the endogeneity concern, we use a regression discontinuity (RD) design that focuses on high-frequency changes in mobility around specific lockdown measures, thereby reducing the risk that other factors may affect mobility at the same time. In addition, we estimate local projections in which we control for pre-existing mobility trends and for the severity of the country's epidemic. We further strengthen the identification by excluding those provinces that experienced early or particularly severe outbreaks. In this case, the analysis looks at the mobility patterns in provinces less affected by COVID-19 for which the adoption of national lockdowns was largely an exogenous event.

The results from the RD design show that the adoption of stay-at-home orders in Italy, Portugal, and Spain led to a sharper contraction in women's mobility relative to men's. Stay-at-home orders coincided in most provinces with school closures. To isolate the impact of school closures on mobility, we narrow the analysis to provinces in Northern Italy that imposed school closures before stay-at-home orders. We find that school closures led already to a considerable gender differential in mobility, highlighting the uneven role of women in caring for children.

The findings based on local projections corroborate the results of the RD analysis, showing that lockdowns had a disproportionate effect on the mobility of women. The differential impact is statistically significant and quantitatively relevant. Among people aged 24 to 45, a full lockdown—including all measures used by governments during the pandemic—reduces the number of women leaving home by almost 26 percent, against an impact on men of about 21 percent.

The local projections also allow to examine the effects of rising COVID-19 cases on mobility for a given level of the stringency of lockdowns. This captures the extent to which people decide to voluntarily limit social interactions when the fear of contracting the virus becomes more acute. Examining this aspect is very important because much of the public debate on the need for lockdowns centers on whether people can autonomously change behavior when infection risks arise. The analysis shows that both men and women significantly reduce mobility when infections increase and they do so with equal intensity.

Regarding the differential effects across age, RD designs show that stay-at-home orders disproportionately reduce the mobility of working age people, especially those below 45 years of age. Local projections provide additional evidence that lockdowns have a larger impact on younger cohorts. These findings are concerning because younger workers generally rely on labor income to support consumption, while older

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people have access to personal savings and possibly retirement income. Furthermore, younger workers often have less stable job contracts that are more likely to be terminated during a crisis. Survey based evidence confirms that younger people have been more likely to suffer an income loss during the pandemic (Belot et al., 2020; Montenovo et al., 2020). The fact that lockdowns impose a disproportionate economic burden on the young—while protecting mostly the old given the higher health risks— calls for policy intervention to ensure inter-generational fairness (Glover et al., 2020).

Using local projections, we also explore if people of different age respond differently to rising infections. Because COVID-19 poses much greater risks for people aged 65 and above, it could be expected that these people are more likely to isolate themselves when infections rise. On the contrary, the analysis shows that younger people reduce mobility more strongly when infections increase. This is consistent with survey level evidence presented by Bordalo et al. (2020) showing that younger people are more alarmed by the risk of contracting COVID-19.

The paper is structured as follows. Section 2 presents background information on the COVID-19 crises in Italy, Portugal, and Spain, and the relative containment measures. Section 3 describes the data provided by Vodafone. Section 4 and 5 present the analysis of the mobility patterns by gender and age, respectively. Section 6 examines the robustness of the results. Section 7 concludes.

2 The COVID-19 crises in Italy, Portugal, and Spain

In this section we describe the evolution of the COVID-19 crises in Italy, Portugal, and Spain and the lockdown measures adopted at the local and national level.

Italy. Italy was among the first countries to be hit by COVID-19 after China. On January 31, the Italian government declared a state of emergency and stopped flights from and to China. Apart from two Chinese tourists who were promptly isolated, there was no confirmed case until February 21 when a patient with anomalous pneumonia was diagnosed with COVID-19 in Codogno, Lombardy. Shortly after that, new cases were discovered in other towns in Lombardy and Veneto. On February 22, a decree imposed the quarantine of more than 50,000 people from 11 municipalities (*comuni*) in Northern Italy (so called *zone rosse*). In other areas of Emilia-Romagna, Lombardy, and Veneto (*zone gialle*) schools, theatres, clubs, and cinemas were closed and social and sports events were suspended. On March 4, all schools and universities across Italy were closed for two weeks and all sporting events could be played only behind closed doors until April 3. As the outbreaks continued and the number of deaths soared, on March 8, all 12 provinces in Lombardy and 14 provinces in Piedmont, Emilia-Romagna, Veneto, and Marche, were put under lockdown. Two days later, the lockdown was extended to the whole country. Steep penalties were announced for violators, including the possibility of three months of imprisonment. On March 11, the government prohibited almost all commercial activities except for supermarkets and pharmacies. On March 21, all non-essential businesses and industries were closed, and movement of people was restricted. In May, many restrictions were progressively eased. Freedom of movement across regions and other European countries was restored on June 3.

Portugal. The first cases of COVID-19 in Portugal were recorded on March 2. On March 18, the entire Portuguese territory entered in a State of Emergency, which lasted until May 2. During the Easter week (April 9 to 13), the government decreed special measures to restrict people movements between municipalities (*concelhos*) with few exceptions, closing all airports to civil transportation. On May 4, restrictions started to be eased and small stores reopened. On May 18, nurseries, the last two years of the secondary school, restaurants, cafes, medium-sized stores and some museums reopened.

Spain. The first case of a patient with COVID-19 in Spain was a foreign tourist on January 31. Broader diffusion began by mid-February and all 50 provinces had confirmed cases by mid-March. A lockdown was imposed on March 14. Starting March 30, all non-essential workers were ordered to remain at home for the next two weeks. COVID-19 spread rapidly and by March 25, the official death toll in Spain surpassed that of China with most cases concentrated in Madrid. The number of deaths peaked in early April and progressively declined until June 1 which was the first day without COVID-19 related deaths. The first local lockdown was announced on March 7 for a small municipality. On March 12, the lockdown was extended to four municipalites in Catalunya with 70,000 people affected. On March 14, the entire country entered in the state of emergency and many nonessential activities were closed, such as restaurants and museums. Citizens were still permitted to travel to work and buy essential items. The authorities in some autonomous communities, including the Basque Country, Murcia, Balearic Islands, Catalunya, announced additional emergency measures. On March 28, all non-essential workers were ordered to stay home from March 30 to April 9. Progressive easing of the lockdown started at the beginning of May. On May 11, the opening of small shops, of terraces at half capacity, and of places of worship at one-third capacity was allowed in 26 provinces and territories comprising about half of the population.

3 A unique dataset

We use anonymized and aggregated data on mobility provided by Vodafone through a confidential agreement. By analysing connections of mobile phones to cell towers, Vodafone can create mobility indexes differentiated across gender and age groups using the information that customers provide when signing up for post-paid contracts.[1] The age groups include four categories: people aged between 18 and 24, between 25 and 44, between 45 and 64, and 65 and above.[2] For Spain and Portugal, however, some daily observations are missing, especially for the oldest and youngest age groups. In these cases, we linearly interpolate the series to have a balanced panel throughout the sample period.

The mobility indicator used in the analysis captures the percentage of people in a given province and demographic group that leaves home in a day. The home location of each customer is identified by monitoring cell connections during the night. The top 3 cells that a phone connects to between 10pm and 5am are considered as home cells. A customer is recorded as leaving home if the phone connects to a cell different from the home cells. More details on the data construction are provided in Lourenco et al. (2020).

The mobility patterns detected by Vodafone are broadly in line with those according to Apple and Google data.[3] Figure 1 shows that all indicators correlate fairly closely at the national level. Correlations

[1] These indicators were prepared by Vodafone's Big Data and Artificial Intelligence team. To protect the privacy of individuals and minority groups, the data have been provided in anonymized form, reporting the average mobility for a given gender and age group at the provincial (NUTS3) level when a minimum of 50 customers are available. Furthermore, the data sharing protocol was subject to technical and organizational controls including an ethical assessment of the analysis prior to its implementation.

[2] In a few cases, the age information is inferred. For example, in Spain, the age group 18–24 is separated from family contracts based on several factors, including the amount of data used. Furthermore, in Portugal customers' age is based on the sequential number of personal identification cards that allow to infer people's age with an error of five years at most.

[3] Apple mobility data are available at https://covid19.apple.com/mobility, and Google mobility data are available at https://www.google.com/covid19/mobility.

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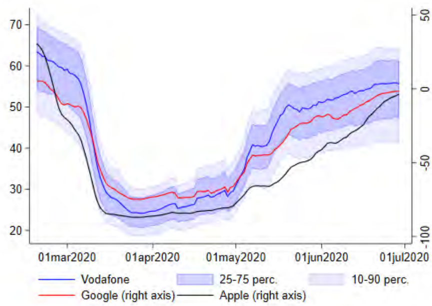
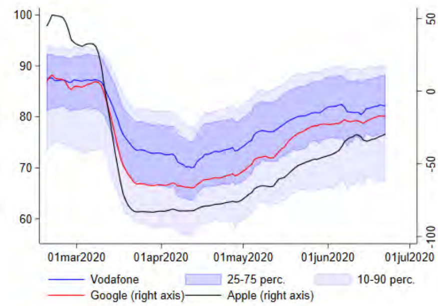
between the Vodafone indicator and the Apple and Google indicators range between 93 and 99 percent for Italy and Portugal and are 72 and 88 percent for Spain. The geographical disaggregation of the Vodafone data allows to appreciate the heterogeneity across provinces. In all the three countries, the interdecile range of the mobility indicator is as large as 20 percentage points. Yet, such dispersion remains broadly constant over time.

Figure 1: Mobility Levels from Apple, Google, and Vodafone

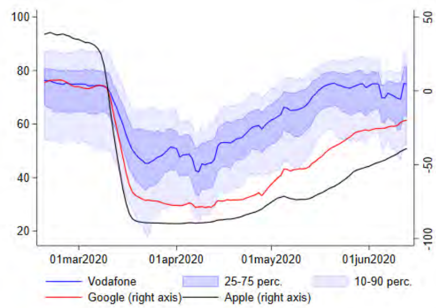
(a) Italy



(b) Portugal



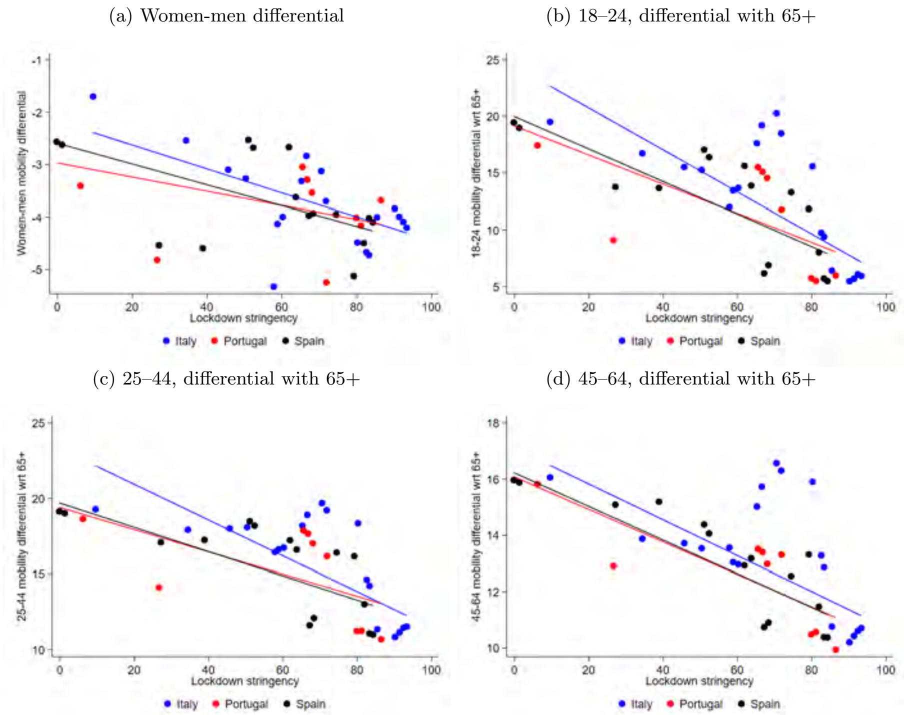
(c) Spain



Notes: The lines denote the country-level mobility levels. In the case of Vodafone, the line corresponds to the cross-province population-weighted average of the percent of people moving, using 2018 population levels as weights; and the shaded areas denote the cross-province interquartile range (dark blue) and the cross-province interdecile range (light blue). In the case of Google, the line corresponds to the average of country-level mobility indicators at retail, grocery, parks, transit, and workplace locations, where mobility is defined relative to pre-crisis levels. And in the case of Apple, the line denotes the country-level indicator of mobility, which is computed from the number of requests made to Apple Maps for directions.

The key advantage provided by the Vodafone data is the ability to differentiate mobility across gender and age groups. This makes it possible to examine whether lockdowns have heterogeneous effects on people's mobility depending on gender and age. Figure 2 provides preliminary evidence in this regard. Panel 2a shows for each country the correlation between the stringency of lockdowns during the period of analysis and the average mobility differential between women and men. In all countries lockdowns have been associated with a larger drop in women' mobility relative to men's. The other three panels in Figure 2 show the correlation between the stringency of lockdowns and the mobility differential relative to the oldest age category of 65 and above. The charts suggest that lockdowns reduce more strongly the mobility of working age people relative to people aged 65 and above. The rest of the analysis will test more formally for these patterns using RD approaches and local projections.

Figure 2: Mobility and Lockdown Stringency



Notes: Panel (a) presents a binned scatter plot showing the mobility differential between women and men over the stringency of lockdowns during the period of analysis. Panel (b) to (d) present similar scatter plots but considering the differential in percentage points between people in different age groups relative to people aged 65 and above. Each dot denotes the cross-province average at any given time. The mobility indicator is residualized with respect to days of the week fixed effects. The lines denote the linear fit.

4 Heterogeneous effects on mobility across gender

In this section, we examine whether lockdowns have a different effect on the mobility of women and men. Assessing the impact of lockdowns on mobility is a challenging task because the decision to deploy lockdowns is not random. For example, governments are more likely to impose lockdowns when health risks become more acute. At that time, people voluntarily reduce social interactions because they fear being infected or infecting others. If voluntary social distancing is not controlled for, the empirical analysis would thus

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overplay the impact of lockdowns on mobility. Policymakers may also impose lockdowns when mobility is too high, thus leading to a spurious association between lockdowns and high mobility.

To alleviate these endogeneity concerns we use two empirical strategies. First, we employ RD designs that focus on high-frequency changes in mobility around specific lockdown measures, thus reducing the risk that other factors may affect mobility at the same time. Second, we use local projections that control for lagged mobility and for the severity of the country's epidemic based on the number of new infections. To further strengthen identification, local projections are estimated using data from provinces that did not experience severe outbreaks and thus for which the adoption of national lockdowns was mostly an exogenous event. The use of local projections is also helpful to examine how people voluntarily reduce mobility in response to rising infections.

4.1 Regression discontinuity

To test whether lockdowns have unequal effects across gender, we first use an RD approach in a similar spirit to Davis (2008), Anderson (2014), and Chetty et al. (2020). With respect to a standard cross-sectional RD setting, in this case the running variable is time and the treatment date is a particular temporal threshold, making this approach akin to an event study exercise. As in more standard RD, endogeneity is addressed by considering a narrow bandwidth (in this case a time window) around the introduction of the treatment. The identification assumption is that, within this interval, unobserved confounding factors affecting the outcome variable are likely to be similar. In our context, this means that no other factors affecting mobility should change close to national stay-at-home orders.[4]

Figure 3 uses a bin scatter plot to present preliminary evidence that lockdowns are associated with a discontinuity in the mobility of women relative to men. Each dot represents the average mobility levels of men and women calculated using 20 equally sized bins around the introduction of national stay-at-home orders. We start by considering people aged between 25–44 for whom the differential effect of lockdowns across gender is the greatest, as we will later show. Mobility data are residualized with respect to province and day-of-the week fixed effects. The figure shows that the introduction of stay-at-home orders led to a sharp drop in the mobility of both men and women. The percentage of people living their homes in a day declined by about 15 points. Yet, the impact on women was stronger, as their mobility declined by about 3 percentage points more than for men.

In most provinces, the adoption of stay-at-home orders coincided with or rapidly followed the decision to close schools. Therefore, the gender gap in Figure 3 could be driven by women carrying a disproportionate burden in caring for children when they are at home. To shed light on this aspect, we take advantage of the fact that five regions in Northern Italy closed schools well in advance of the national stay-at-home order.[5] Using mobility data from provinces in Northern Italy, Figure 4a presents an RD exercise with two discontinuities: the first is set on February 23, the day when local schools closed, and the second one on March 9, when the national lockdown was implemented. The divergence in mobility between men and women started already at the time of school closures. Men's mobility declined very marginally when schools closed, while women's mobility saw a clear discontinuity. This corroborates the hypothesis that women carry uneven

[4] Of course, the number of contagions surged in the weeks leading to the stay-at-home orders, which were imposed because of this surge. However, the identifying assumption is that there was no discontinuity in the number of cases in the day of the orders. To test if this assumption is valid, we did an RD on cases at the time of lockdowns. There is no clear discontinuity.

[5] Schools in Northern Italy closed on February 23. On March 4, the Italian government closed all schools and universities nationwide. The national stay-at-home order was announced with a Presidential Decree on March 9.

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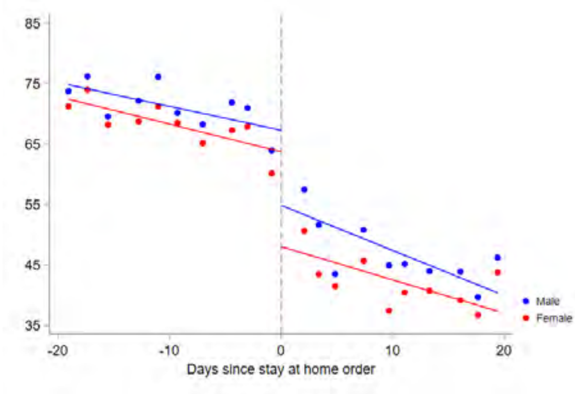
Figure 3: Impact of Stay-at-Home Orders on Mobility, by Gender
(Age group 25–44, percentage of people moving)



Notes: The chart shows the percentage of men and women moving divided into 20 equal-sized bins. The series are residualized with respect to province and day-of-the-week fixed effects.

responsibilities in looking after the children when schools are closed.

Figure 4b provides additional evidence about the importance of school closures by examining the mobility gender gap across all provinces in Northern Italy. The heat map reports the difference between the mobility of men and women through time, with darker colors representing a decline in women's mobility relative to men's. The mobility of men and women was similar before February 23. When schools closed, the heat map shows darker colors across all provinces, reflecting a disproportionate reduction in women's mobility. The adoption of stay-at-home orders led to a further widening of the mobility gap.[6]

[6]Figure 4b provides also an additional insight. The provinces in figure 4b are listed in order of decreasing frequency of COVID-19 cases as a share of the province population on March 9. The absence of a clear vertical pattern indicates that the effects of school closures and lockdowns on the difference in mobility across gender was not correlated with the local intensity of the COVID-19 crisis.

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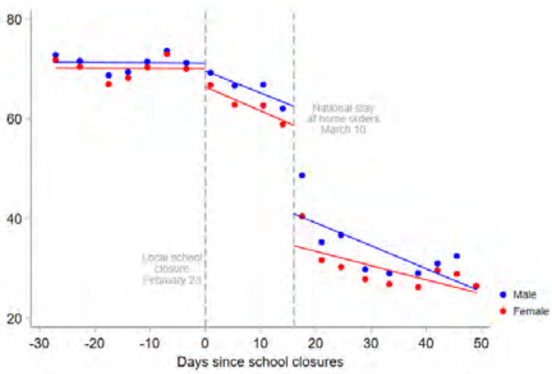
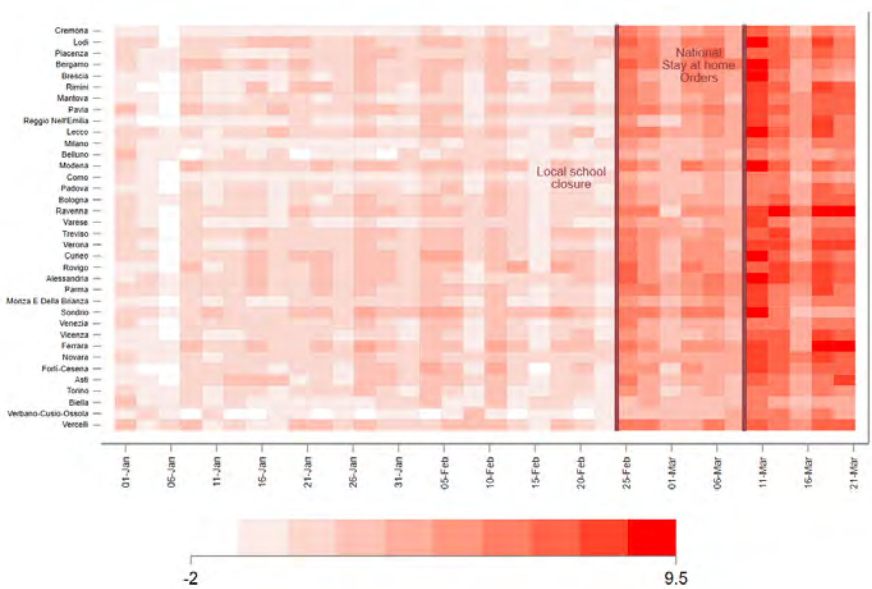
Figure 4: Impact of School Closures and Stay-at-Home Orders in Northern Italy
(Age group 25–44, percentage of people moving)

(a) Average impact across provinces



(b) Impact across each provinces



Notes: Panel (a) reports a binned scatter plot where the percentage of people moving is divided into 20 equal-sized bins. The series are residualized with respect to province and day-of-the-week fixed effects. Panel (b) reports the difference between men and women mobility in Friuli-Venezia-Giulia, Emilia-Romagna, Lombardia, Piemonte, and Veneto. Local school closures were introduced on February 23rd, and national stay-at-home orders on March 9th.

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The differences in drop in mobility across age groups further confirm that school closures impacted disproportionately women's mobility. The analysis presented so far has focused on people aged between 25 and 44. These cohorts are more likely to have young kids that require home supervision when schools are closed.[7] A natural test of our conjecture is to test if the mobility gap was different for other age ranges.

To analyze the impact of lockdowns on the gender gap across all age groups and to test for the statistical significance of the discontinuity at the time of the lockdown, we follow Anderson (2014) and estimate this local linear regression:

$$\begin{aligned} mob_{i,g,a,t} &= \alpha_p + \tau_{dow} + \beta stay_{j,t} + \phi women_i + \gamma date_{j,t} \\ &+\theta stay_{j,t} \times date_{j,t} + \lambda women_{i,a} \times stay_{j,t} + \nu date_{j,t} \times women_i + \varepsilon_{i,g,a,t} \end{aligned} \tag{1}$$

where $mob_{i,g,a,t}$ is the mobility indicator provided by Vodafone capturing the percentage of people moving in province i, of gender g and age group $a = \{[18, 24]; [25, 44]; [45, 64]; [65+]\}$, at time t; $stay_{j,t}$ is the treatment variable for country j (with $i \in j$), equal to one when the national stay-at-home orders are in place; $women_{i,a}$ is a dummy variable equal to one when the dependent variable refers to the mobility of women; $date_{j,t}$ is the number of days since the introduction of the stay-at-home order; and α_p and τ_{dow} are province and day-of-the-week fixed effects. The coefficient β captures the effect of the stay-at-home orders on men's mobility, while $\lambda + \beta$ traces the effect on women's mobility. Standard errors are clustered at the province level. The identification assumption is that the term $stay_{j,t} \times date_t$ should absorb any smooth relationship between the $date_{j,t}$ and the error term $\varepsilon_{i,g,a,t}$ in the days around the introduction of the lockdown (Anderson, 2014). This means that no other factor affecting mobility should change close to the national stay-at-home orders. Consistent with Figure 3, we estimate equation (1) using a relatively narrow window of 20 days around the adoption of stay-at-home orders since our identification strategy aims at estimating β and $\lambda + \beta$ by considering the mobility drop close to the introduction of lockdowns.

Table 1 reports the results for the baseline model. Column (2) shows that the mobility of women aged 25–44 declined by 3 percentage points more than men's when stay-at-home orders were imposed which coincided in most provinces with school closures. Column (1) and (3) present the results of the same specification for the age groups 18–24 and 45–64: the gap between women and men mobility is still present, statistically significant, but smaller, equal to 2.3 and 1.7 percentage points respectively. Finally, Column (4) shows that lockdowns no longer have a disproportionate effect on the mobility of women in the age group 65+. These results show that the mobility gender gap is the largest for people aged 25–44 that are more likely to have young children. Therefore, they suggest that childcare needs largely explain the disproportionate impact of lockdowns on women's mobility.

4.2 Local projections

The RD approach used in the previous section shows that the adoption of specific lockdown measures reduced the mobility of women more forcefully. We now check if similar results hold when using local projections that exploit the entire variation in the stringency of lockdowns over the period of analysis.

To alleviate endogeneity concerns about lockdowns—namely that they are more likely imposed when

[7]In Italy, as in other countries, grandparents often play an important role in taking care of the kids while parents work. However, because COVID-19 affects disproportionately old people, social contacts between old and young people were discouraged. Therefore, the traditional arrangement was possibly less used, magnifying the effect of school closures on parents' mobility.

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Table 1: RD Estimate of the Gender Gap by Age Group

	18–24 (1)	25-44 (2)	45–64 (3)	65+ (4)
Stay-at-home	-19.60***	-12.95***	-12.52***	-11.76***
	(0.59)	(0.46)	(0.41)	(0.46)
Women × stay-at-home	-2.31***	-3.24***	-1.74***	1.55***
	(0.50)	(0.35)	(0.34)	(0.57)
Observations	13,909	14,102	14,151	13,102
R-squared	0.87	0.86	0.87	0.82

Notes: The table reports the coefficient on the stay-at-home variable and the coefficient on the interaction between the gender dummy and the stay at home variable. All regressions include the gender dummy, a variable for the number of days since the introduction of the stay-at-home order, the interaction terms of the latter with the stay-at-home variable and with the gender dummy, and province and day-of-the-week fixed effects. Standard errors are clustered at the province level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

the epidemic is worsening and when mobility is too high—the local projections control for the number of COVID-19 infections and for lagged mobility levels to capture pre-existing trends. Furthermore, we rely on an identification strategy that takes advantage of the disaggregation of the Vodafone mobility data at the NUTS-3 level. Italy, Portugal, and Spain imposed lockdowns on a *national* scale in reaction to *localized* outbreaks. For example, in Italy the government imposed a national lockdown in early March even though most of the infections were concentrated in a few provinces in Lombardy. Therefore, the adoption of national lockdowns was largely exogenous to the conditions prevailing in provinces with relatively low infections. Leveraging on this observation, we exclude from the regression sample of each country the provinces that (i) registered the first 100 (cumulative) cases, (ii) had the highest number of COVID-19 cases by the end of June 2020, and (iii) that had more than five percent of the country's total confirmed cases when the lockdown stringency index reached its maximum.[8] The regression thus examines the mobility response in the regions less affected by the virus for which the national lockdown was an exogenous event triggered by conditions elsewhere in the country.

Formally, to assess the differential impact of lockdowns on women's mobility, we estimate the following local projection regressions (Jordà, 2005) using data for a particular age group:

$$mob_{i,g,a,t+h} = \alpha_i^h + \kappa_g^h + \tau_t^h + \sum_{p=1}^{P} \rho_p^h mob_{i,g,a,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{j,t-p} + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p}$$
$$+ women_{i,a} \times \left(\sum_{p=0}^{P} \gamma_p^h lock_{j,t-p} + \sum_{p=0}^{P} \psi_p^h ln\Delta cases_{i,t-p} \right) + \varepsilon_{i,g,a,t+h} \quad (2)$$

where variable $mob_{i,g,a,t+h}$ denotes the percentage of people moving in province i, of gender g and age a, at time $t+h$, with $h = \{1, \ldots, 20\}$ being the horizon; $ln\Delta cases_{i,t-p}$ is the log of daily COVID-19 cases, which

[8]These criteria lead to the exclusion of Bergamo, Brescia, Lodi, Milan, Torino, and Rome in Italy; Barcelona and Madrid in Spain; and Área Metropolitana do Lisboa, Área Metropolitana do Porto, Cávado, and Região de Aveiro, Tâmega e Sousa in Portugal. Adding these areas back into the sample does not affect the results as shown in the robustness section.

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is used to track the stage of the pandemic, with p being the lag length (set to a week to control for the persistence of the variable); and $lock_{j,t-p}$ is an index measuring the stringency of lockdowns for country j (with $i \in j$), which also enters the specification with p lags to account for persistence.[9] The specification also features lags of the dependent variable to control for pre-existing trends; province and gender fixed effects to capture time-invariant characteristics specific to provinces, men, and women; and time-fixed effects to control for those factors that are common to all provinces. Standard errors are clustered at the province level.

To uncover the differential impact of lockdowns on women, we include an interaction term between the lockdown stringency index and a gender dummy $women_{i,a}$, which is equal to one when the dependent variable refers to the mobility of women. Thus, the coefficient δ_0^h isolates the impact of lockdowns on men's mobility and $\delta_0^h + \gamma_0^h$ the one on women's mobility. The regressions are estimated on a sample of 163 provinces in Italy, Spain, and Portugal between January 1 and June 29, 2020.

Figure 5 shows the impact of a full lockdown that includes all measures used during the pandemic—among which travel restrictions, school and business closures, and stay-at-home orders—on the mobility of men and women aged 24 to 45. The responses in panel 5a show that a full lockdown leads to a very significant decline in mobility for both men and women. Mobility starts to decline when the lockdown is introduced, reaching the through after seven days. Mobility gradually resumes afterwards as the lockdown stringency impulse dissipates, as shown in Figure A.1 of Appendix A.

Most importantly, panel 5a reveals that lockdowns have an uneven effect on mobility across gender, impacting women more strongly. Women's mobility falls by 26 percentage points seven days after the introduction of lockdowns, while that of men declines by about 21 percentage points. Panel 5b shows that the differential between the mobility of women and that of men is statistically significant until the lockdown impulse weakens 15 days after the initial tightening.

These results corroborate the findings of the RD analysis that lockdowns tend to impact women disproportionately. The RD analysis also showed that the gender differential is the largest for people aged 25–44, probably because they are more likely to have young children that have to be supervised at home when schools are closed. To check for the robustness of these findings, we re-estimate the local projections for the age groups 18–24, 45–64, and 65+. Table 2 reports the largest mobility gap between women and men in response to a full lockdown over the 20-day horizon of the local projections. We confirm that women's mobility falls the most relative to men's for people aged 25–44, with a differential of 4.7 percentage points. The gender gap declines to 3.6 percentage points for people aged 18–24 and to 3.7 percentage points for those aged 45–64. For people in the age group 65+, the fall in women's mobility is statistically indistinguishable from the men's one. These results are thus closely aligned with those of the RD analysis.

Besides capturing the impact of lockdowns, the local projection in equation (3) also measures how mobility responds to an increase in COVID-19 infections holding constant the stringency of lockdowns. This is an important issue because during the pandemic people voluntarily reduced exposure to each other as they feared contracting the virus. For example, Aum et al. (2020), Goolsbee and Syverson (2020), and Maloney and Taskin (2020) document that mobility was tightly correlated with the spread of COVID-19

[9] We use the lockdown stringency index provided by the University of Oxford's Coronavirus Government Response Tracker. This index is a simple average of nine sub-indicators capturing school closures, workplace closures, cancellations of public events, gatherings restrictions, public transportation closures, stay-at-home requirements, restrictions on internal movement, controls on international traveling, and public information campaigns, both at the subnational and national level. Since we want to measure the impact of *actual* restrictions at the national level, we re-construct the index excluding public information campaigns (as they aim to promote voluntary social distancing) and considering only measures that were adopted at the national level.

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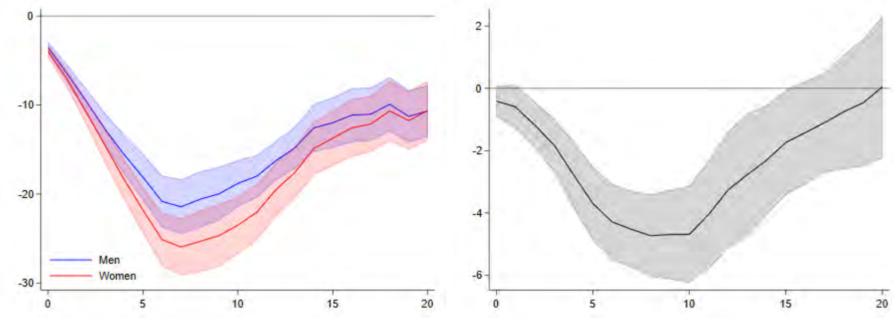
Figure 5: Impact of a Full Lockdown on Mobility, by Gender
(Age group 25–44, percentage of people moving)

(a) Men vs Women (b) Women-men differential



Notes: The x-axes denote the number of days, the lines denote the point estimates, and the shaded areas correspond to 90 percent confidence intervals computed with standard errors clustered at the province level.

Table 2: Gender Gap at the Trough of the Estimated Response

	18–24 (1)	25-44 (2)	45–64 (3)	65+ (4)
Lockdown stringency	-27.07***	-20.60***	-19.75***	-15.19***
	(1.80)	(1.60)	(1.57)	(1.77)
Women × lockdown stringency	-3.58***	-4.73***	-3.69***	2.33
	(0.95)	(0.67)	(0.73)	(1.46)
Days after the shock	7	7	7	7
Observations	18,798	18,798	18,830	17,872
Provinces	163	163	163	157
R-squared	0.94	0.94	0.94	0.91

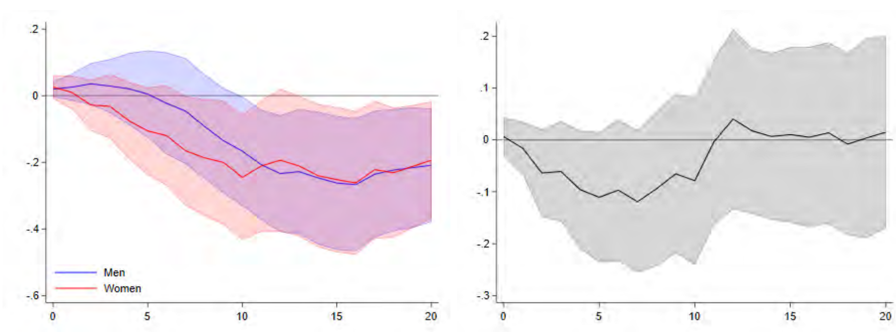
Notes: The table reports the coefficient on lockdown stringency and the coefficient on the interaction term between the gender dummy and lockdown stringency at the trough of the estimated response. All regressions include the contemporaneous value and/or seven lags of the stringency index, the log of daily cases, the interaction between a gender dummy and the stringency index, and province, gender, and time fixed effects. Standard errors are clustered at the province level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

even after controlling for government lockdowns. In line with this literature, the specification in equation (2) sheds light on the strength of voluntary social distancing by capturing the response of mobility to rising COVID-19 infections for a given lockdown stringency.[10] The interaction term between daily COVID-19 infections and the gender dummy reveals if the extent of voluntary social distancing differs between men and women. Specifically, the coefficient β_0^h measures the extent of voluntary social distancing for men, while the coefficients $\beta_0^h + \psi_0^h$ reflect the response of women.

Figure 6 shows how mobility responds to rising COVID-19 infections for a given lockdown stringency. An increase in COVID-19 cases has a negative effect on the mobility of both men and women. A doubling of daily COVID-19 cases leads to a contraction in mobility by about 0.3 percentage points 20 days after the introduction of the lockdowns. The effect is similar across men and women. Panel 6b shows indeed that there is no statistically difference across gender in how mobility responds to rising infections.

Figure 6: Impact of a Doubling of COVID-19 Cases on Mobility, by Gender
(Age group 25–44, percentage of people moving)

(a) Men vs Women (b) Women-men differential



Notes: The x-axes denote the number of days, the lines denote the point estimates, and the shaded areas correspond to 90 percent confidence intervals computed with standard errors clustered at the province level.

[10]Besides reacting to the spread of COVID-19, people may opt to voluntarily self distance also in response to other factors, such as public health announcements, news about celebrities being infected, or even the adoption of government lockdowns. As such, the analysis may underestimate the true extent of voluntary social distancing. Also, as shown by Adda (2016), higher mobility might lead to faster spread of viral diseases, generating some reverse causality between the outcome variables and COVID-19 infections. The dynamic structure of the estimation should alleviate this endogeneity concern.

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5 Heterogeneous effects on mobility across age groups

In this section, we examine if lockdowns have a different impact on mobility depending on people's age. In line with the analysis on the effects across gender, we first examine the data using an RD approach. We then revisit the evidence using local projections which also allow us to examine if people respond differently to rising infections depending on their age.

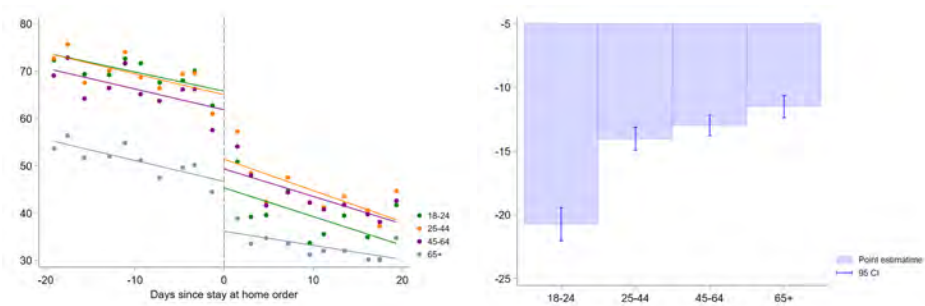
5.1 Regression discontinuity

We study the impact of stay-at-home orders on different age groups using the RD framework described in section 4.1. Panel 7a shows graphical evidence of the impact of stay-at-home orders on the mobility of each age group. Each dot captures the average mobility of both women and men in a given age group from 20 days before to 20 days after the adoption of stay-at-home orders. We see that lockdowns drastically reduced people's mobility across all age groups.

Yet, the mobility drop was significantly stronger for younger cohorts. This is more clearly illustrated in panel 7b which shows the estimated mobility contraction for each age group using an RD specification akin to 1, with the associated 90 percent confidence intervals. The percentage of people below 25 years of age leaving home in a day declined by more than 20 points when stay-at-home orders were imposed. The mobility drop becomes progressively smaller for older people, being equal to only 11 percentage points for people aged 65 and above.

Figure 7: Impact of a Stay-at-Home Orders on Mobility, by Age
(Percentage of people moving)

(a) Regression discontinuity (b) Estimated impacts



Notes: Panel 7a presents a binned scatterplot where the people moving is divided in 20 equally sized bins. The series is residualized with respect to province, gender day-of-the-week fixed effects. Panel 7b reports the estimates of the percentage drop in people moving by age group. Standard errors are clustered at the province level. See also table 5.

These results show that lockdowns tend to disproportionally impact the mobility of younger cohorts. This is not surprising if we consider that the mobility of people aged 65 and above—most of whom are retirees—was already significantly lower prior to lockdowns, as illustrated in panel 7a. Younger people have instead to leave their homes on a daily basis to reach their work places and bring children to schools. Therefore, they are much more affected by lockdowns that, by impeding movements, have more adverse effects on their employment opportunities.

5.2 Local projections

We now assess the impact of lockdowns across age groups using local projections based on the same identification strategy discussed in Section 4.2. Thus, the local projections control for the number of COVID-19 infections, lagged mobility, and are estimated using data from provinces that did not experience early and/or major outbreaks and thus for whom the adoption of national lockdowns was largely exogenous. Formally, we estimate the following specification:

$$mob_{i,g,a,t+h} = \alpha_i^h + \kappa_a^h + \tau_t^h + \sum_{p=1}^{P} \rho_p^h mob_{i,g,a,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{j,t-p} + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p}$$
$$+ \sum_{a=1}^{3} agegroup_i^{a,g} \times \Big(\sum_{p=0}^{P} \gamma_p^{s,h} lock_{j,t-p} + \sum_{p=0}^{P} \psi_p^{s,h} ln\Delta cases_{i,t-p} \Big) + \varepsilon_{i,g,a,t+h} \quad (3)$$

The specification features interaction terms between the lockdown stringency index and age group dummies $agegroup^a_{i,g}$, with $a = \{1 = [18, 24]; 2 = [25, 44]; 3 = [45, 64]\}$, where the excluded category is the age group 65+. Hence, the impact of lockdowns on the mobility of people aged 65+ at horizon h is captured by δ_0^h, while the impact on the other age groups a is given by $\delta_0^h + \gamma_0^{a,h}$. The specification also includes interaction terms between COVID-19 infections and age groups to test whether the strength of voluntary social distancing differs across age. For a given level of lockdown stringency, the impact of rising COVID-19 cases on the mobility of people aged 65+ is measured by β_0^h, and the one on other age groups by $\beta_0^h + \psi_0^{a,h}$.

Figure 8 shows the effects of lockdowns on the mobility of different age groups. As shown in panel 8a, mobility declines sharply across all age categories during the first ten days after the introduction of a lockdown. Yet, the younger cohorts experience a considerably larger drop in mobility, reaching a trough of 30 percentage points nine days after the introduction of lockdowns for people aged 18–24.[11]

To illustrate the differences across age groups more clearly, panel 8b shows the mobility differential of each age group relative to people aged 65+. The mobility differential of those aged 18–24 compared to people 65+ is the largest and becomes statistically significant since the beginning of the projection horizon. The drop in mobility for the age groups 25–44 and 45–64 becomes statistically larger relative to people 65+ a few days after the lockdown stringency impulse. These findings corroborate the results from the RD analysis in the previous section, showing that lockdowns impact the mobility of younger cohorts disproportionally.

The local projections also shed light on whether the extent of voluntary social distancing differs across age groups. Panel 9a shows that the youngest cohorts react most forcefully to a rise in infections. A doubling of COVID-19 cases leads to a fall in mobility by about one percentage point after 20 days for people aged 18–24. A rise in infections leads also to reduction in mobility for people aged 25–44 and 45–64, even though the effect is more modest. Mobility remains instead broadly unchanged for people aged 65+, actually increasing marginally towards the end of the projection horizon. Panel 9b confirms that mobility declines more for all working-age groups relative to people 65+.

These results are somewhat surprising because people aged 65+ face much greater health risks from COVID-19 and should thus be more prone to isolate themselves when infections increase. Two considerations

[11] The mobility dynamics reflect the underlying impulse to the lockdown stringency that dissipates after two weeks as illustrated in Figure A.1a of Appendix A.

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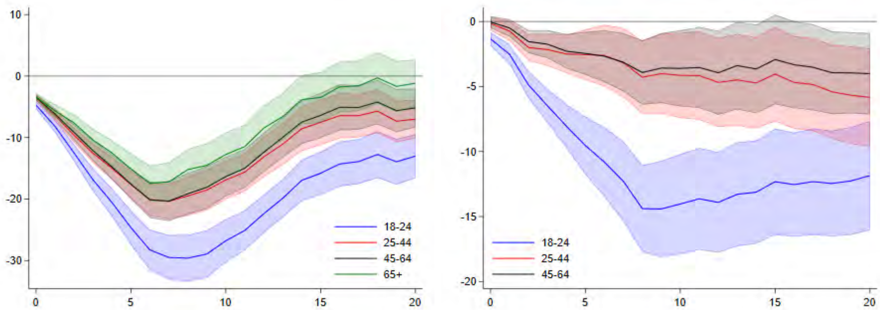
Figure 8: Impact of a Full Lockdown on Mobility, by Age Group
(Percentage of people moving)

(a) Age groups (b) Differential with 65+

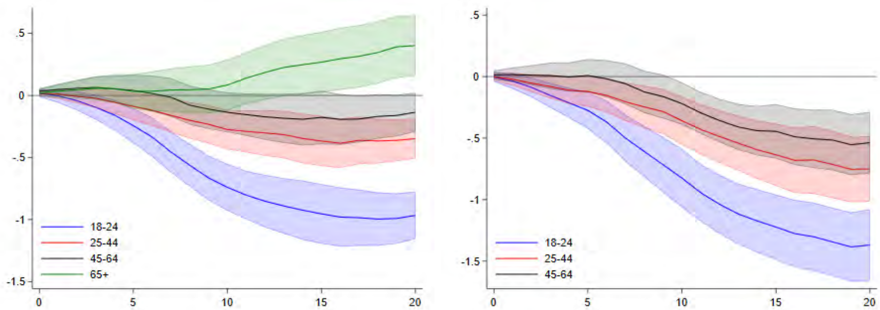


Notes: The x-axes denote the number of days, the lines denote the point estimates, and the shaded areas correspond to 90 percent confidence intervals computed with standard errors clustered at the province level.

may explain our findings. First, the rise in infections reduces business activity in contact-intensive businesses, such as bars and restaurants, as people fear becoming infected. This in turn reduces employment in those sectors where many young people tend to work. Second, the larger response in the mobility of the young may reflect their stronger concerns about the virus. This is consistent with the evidence presented in Bordalo et al. (2020). Based on a survey of 1,500 Americans in May 2020, they find that perceptions about the health risks posed by COVID-19 decline sharply with age. The fact that younger generations seem more sensitive to the fear factor—measured as doubling COVID-19 cases—could also reflect that younger generations use more media and social media which emphasize the danger.

Figure 9: Impact of a Doubling of COVID-19 Cases on Mobility, by Age Group
(Percentage of people moving)

(a) Age groups (b) Differential with respect to 65+



Notes: The x-axes denote the number of days, the lines denote the point estimates, and the shaded areas correspond to 90 percent confidence intervals computed with standard errors clustered at the province level.

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6 Robustness

In this section we test the robustness of our results along several dimensions. We start by re-examining in Table 3 the impact of lockdowns on mobility across gender for peopled aged 25–44 based on the RD analysis. Column (1) reports the differential impact between women and men from the baseline specification in section 4.1. It shows that lockdowns lead to a disproportionate decline in women's mobility. These results are based on a 20-day window before and after the adoption of stay-at-home orders. In column (2) we show that similar results are obtained if we shrink the regression window to 10 days to further limit possible bias from unobservable confounders. The results are also robust in column (3) to excluding the regions in Northern Italy that introduced lockdown measures, such as school closures, before the national stay-at-home order, as shown in Figure 4a and 4b. In columns (4) and (5) we exclude, one at a time, data for Portugal and Spain for which the mobility series are interpolated. The differential impact on women's mobility is confirmed on these different samples. Finally, in column (6) we control for the moving average of daily COVID-19 at the province level to reduce concerns of omitted confounders that may have a discontinuous effect on the mobility. The inclusion of this control, beyond province and day of the week fixed effects does not alter the results. Finally, since the mobility indicators is bounded between 0 and 100 percent, we verify in column (7) that the results are robust to applying a logistic transformation.

Table 3: Robustness of the RD Results by Gender

	Baseline (1)	10-day window (2)	Excl. North. Italy (3)	Excluding Portugal (4)	Excluding Spain (5)	Controlling for cases (6)	Logistic transformation (7)
Stay at home	-12.95***	-8.99***	-12.82***	-14.42***	-13.04***	-11.69***	-0.62***
	(0.459)	(0.424)	(0.548)	(0.440)	(0.454)	(0.469)	(0.024)
Women × stay-at-home	-3.24***	-3.07***	-3.07***	-3.58***	-3.79***	-3.25***	-0.13***
	(0.353)	(0.431)	(0.442)	(0.403)	(0.149)	(0.352)	(0.018)
Observations	14,102	7,228	11,150	12,052	10,742	14,098	14,291
R-squared	0.86	0.85	0.85	0.84	0.92	0.86	0.87

Notes: The table reports the coefficients of an interaction term between the gender dummy and and stay-at-home variable. All regressions include the gender dummy, a variable for the number of days since the introduction of the stay-at-home order, the interaction terms of the latter with the stay-at-home variable and with the gender dummy, and province and day-of-the-week fixed effects. Column (6) considers a 20-day window and controls for the moving average of daily COVID-19 cases. Standard errors are clustered at the province level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

We also verify if the results are robust across provinces with different characteristics. In Table 4 we re-run the RD analysis splitting the sample depending on whether provinces are above or below the median level of GDP per capita, population density, and population size. Furthermore, we split the sample based on whether provinces as considered rural or not by the Eurostat. Across all these samples, lockdowns continue to have a disproportionate effect on the mobility of women, thus confirming that the results are not driven by provinces with peculiar characteristics.

Following a similar set of robustness tests, Table 5 and Table 6 corroborate the RD findings that lockdowns have a stronger impact on the mobility of younger cohorts.

We also perform various robustness tests for findings of the local projections. As discussed in section 4.2, the local projections are estimated on a sample that excludes provinces with early and/or large outbreaks. While this approach mitigates endogeneity concerns regarding the introduction of lockdowns, it may affect our estimates if lockdowns or voluntary social distancing had different effects on mobility in regions more

Table 4: Robustness of the RD Results by Gender across Provinces

	GDP pc below median (1)	GDP pc above median (2)	Pop. density below median (3)	Pop. density above median (4)	Population below median (5)	Population above median (6)	Rural (7)	Not rural (8)
Stay-at-home	-12.166***	-14.141***	-11.588***	-14.617***	-10.985***	-14.826***	-15.930***	-11.902***
	(0.716)	(0.512)	(0.682)	(0.538)	(0.641)	(0.588)	(0.744)	(0.534)
Women × stay at home	-2.655***	-3.859***	-2.849***	-3.648***	-3.502***	-2.974***	-3.379***	-3.185***
	(0.555)	(0.415)	(0.644)	(0.253)	(0.372)	(0.595)	(0.389)	(0.462)
Observations	7,203	6,899	7,293	6,809	6,992	7,110	3,695	10,407
R-squared	0.861	0.880	0.817	0.915	0.876	0.838	0.881	0.852
NUTS3 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Days of week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the coefficients of an interaction term between the gender dummy and and stay-at-home variable. All regressions include the gender dummy, a variable for the number of days since the introduction of the stay-at-home order, the interaction terms of the latter with the stay-at-home variable and with the gender dummy, and province and day-of-the-week fixed effects. Column (1) and (2) are estimated splitting the sample above and below the median of GDP per capita in a given province for 2018. Column (3) and (4) splits the sample below and above the median of population density as measured by the population per squared km in 2018. Column (5) and (6) reports results splitting the sample below and above the median of population in 2018. Column (7) and (8) reports the coefficients estimated splitting the sample according to whether the province is considered rural or not according to Eurostat. Standard errors are clustered at the province level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5: Robustness of the RD Results by Age

	Baseline (1)	10-day window (2)	Excl. North. Italy (3)	Excluding Portugal (4)	Excluding Spain (5)	Controlling for cases (6)	Logistic transformation (7)
Stay-at-home	-11.515***	-9.107***	-11.015***	-12.346***	-12.707***	-10.486***	-0.515***
	(0.441)	(0.429)	(0.537)	(0.459)	(0.354)	(0.425)	(0.020)
18–24 × stay at home	-9.238***	-6.992***	-8.932***	-10.854***	-9.333***	-9.124***	-0.412***
	(0.505)	(0.461)	(0.630)	(0.468)	(0.464)	(0.502)	(0.020)
25–44 × stay at home	-2.526***	-0.752*	-3.031***	-3.127***	-1.354***	-2.453***	-0.122***
	(0.445)	(0.447)	(0.550)	(0.485)	(0.244)	(0.435)	(0.021)
45–64 × stay at home	-1.482***	0.244	-2.361***	-1.957***	0.708***	-1.421***	-0.063***
	(0.489)	(0.504)	(0.597)	(0.542)	(0.196)	(0.478)	(0.023)
Observations	55,264	28,258	43,456	47,672	42,360	55,248	55,264
R-squared	0.852	0.847	0.838	0.834	0.919	0.857	0.864

Notes: The table reports the coefficients of an interaction term between the age groups dummies and the stay-at-home variable. All regressions include the age group dummy, a variable for the number of days since the introduction of the stay-at-home order, the interaction terms of the latter with the stay-at-home variable and with the age group dummy, and province and day-of-the-week fixed effects. Column (6) considers a 20-day window and controls for the moving average of daily COVID-19 cases. Standard errors are clustered at the province level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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Table 6: Robustness of the RD results by Age across Provinces

	GDP pc below median (1)	GDP pc above median (2)	Pop. density below median (3)	Pop. density above median (4)	Population below median (5)	Population above median (6)	Rural (7)	Not rural (8)
Stay at home	-9.866***	-13.328***	-9.876***	-13.186***	-11.278***	-11.730***	-13.559***	-13.559***
	(0.649)	(0.534)	(0.725)	(0.437)	(0.656)	(0.603)	(0.661)	(0.661)
18-24 × stay at home	-8.307***	-10.188***	-8.359***	-10.327***	-8.069***	-10.405***	-10.039***	-10.039***
	(0.779)	(0.621)	(0.829)	(0.508)	(0.668)	(0.707)	(0.693)	(0.693)
25-44 × stay at home	-3.463***	-1.666***	-2.937***	-2.293***	-0.950*	-4.074***	-3.415***	-3.415***
	(0.748)	(0.434)	(0.799)	(0.352)	(0.549)	(0.648)	(0.541)	(0.541)
45-64 × stay at home	-2.970***	-0.007	-2.978***	-0.087	-0.178	-2.764***	-1.550***	-1.550***
	(0.778)	(0.542)	(0.891)	(0.325)	(0.608)	(0.737)	(0.538)	(0.538)
Observations	27,914	27,350	28,115	27,149	27,089	28,175	14,659	14,659
R-squared	0.854	0.870	0.810	0.908	0.865	0.840	0.876	0.876
NUTS3 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Days of week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the coefficients of an interaction term between the age dummy and and stay-at-home variable. All regressions include the age dummy, a variable for the number of days since the introduction of the stay-at-home order, the interaction terms of the latter with the stay-at-home variable and with the gender dummy, and province, gender and day-of-the-week fixed effects. Column (1) and (2) are estimated splitting the sample above and below the median of GDP per capita in a given province for 2018. Column (3) and (4) splits the sample below and above the median of population density as measured by the population per squared km in 2018. Column (5) and (6) reports results splitting the sample below and above the median of population in 2018. Column (7) and (8) reports the coefficients estimated splitting the sample according to whether the province is considered rural or not according to Eurostat. Standard errors are clustered at the province level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

impacted by the virus. Thus, we test if our findings are robust to the inclusion of those provinces. Figure 10 shows the coefficients on the interaction terms that capture the differential impact of lockdowns and COVID-19 cases on mobility across gender and age groups. Panels 10a and 10b confirm that lockdowns hit women's mobility disproportionately and that voluntary social distancing was broadly similar across gender. Panels 10c and 10d also corroborate the baseline results that lockdowns and voluntary social distancing took a larger toll on younger cohorts. In terms of magnitudes, the estimated effects are virtually identical to those in the baseline.

We also examine if the results are robust to excluding time fixed effects which are used to capture movements in mobility that are common across provinces but are unrelated to the dynamics of lockdown stringency and COVID-19 infections.[12] One could argue that controlling for them in the local projections may saturate the specification given the high-frequency of the data. We thus replace time fixed effects with day-of-the-week fixed effects. Panels 11a and 11b of Figure 11 confirm the disproportional impact of lockdowns on women's mobility compared to men's, as well as that rising infection do not generally have a statistically significant different effect across gender. If anything, the women-men mobility differential in response to lockdowns appear more persistent than with time fixed effects. Similarly, without time fixed effects, panel 11c shows that lockdowns are still found to impact more strongly the mobility of younger people. Finally, panel 11d shows that the baseline findings about the impact of rising COVID-19 cases on the mobility of different age groups are robust to replacing time fixed effects with day-of-the-week fixed effects.

Another possible concern with the local projections is that the results could be affected by the linear interpolation of the missing observations for Portugal and Spain. Thus, we re-estimate the local projections excluding one of these two countries at a time.[13] Figure 12 presents the results of the impact of lockdowns and voluntary social distancing when data for Portugal are excluded. Figure 13 repeats the exercise excluding

[12]Such movements could be caused by public announcements by the government, public health officials, and international organizations, or by news about celebrities being infected.

[13]Running regression with data for a single country would prevent the possibility of including time fixed effects.

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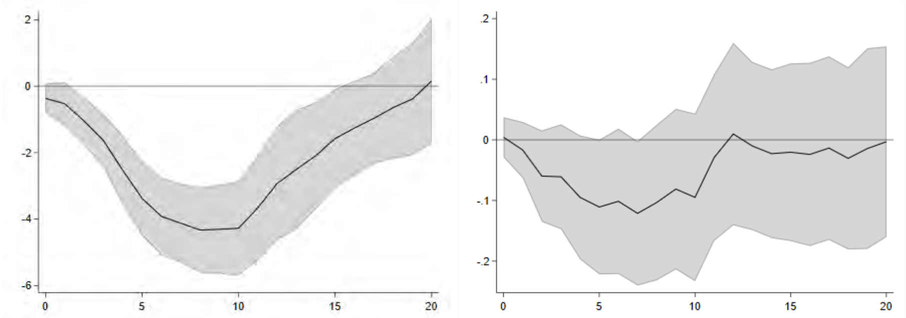
Figure 10: Impact of Lockdowns and COVID-19 Cases using Full Sample
(Percentage of people moving)

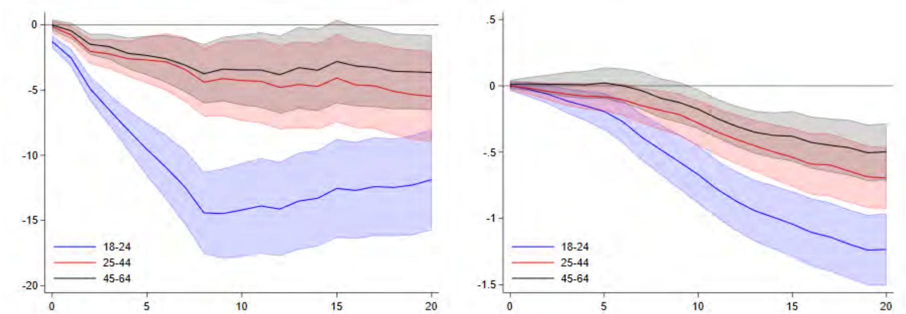
(a) Impact of a full lockdown, women-men differential

(b) Impact of a doubling of COVID-19 cases, women-men differential



(c) Impact of a full lockdown, differential with respect to 65+

(d) Impact of a doubling of COVID-19 cases, differential with respect to 65+



Notes: The x-axes denote the number of days, the lines denote the point estimates, and the shaded areas correspond to 90 percent confidence intervals computed with standard errors clustered at the province level.

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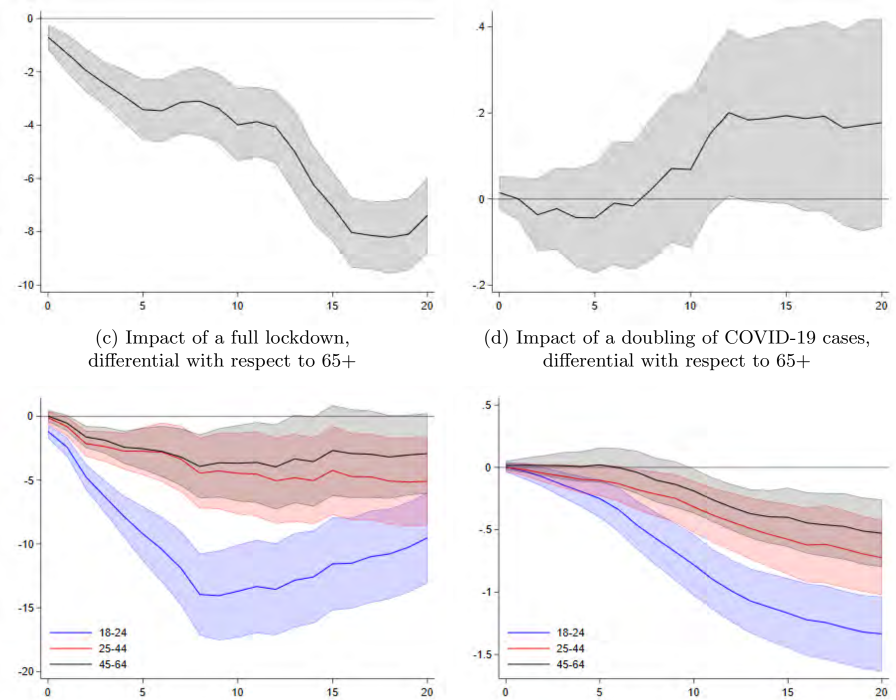
Figure 11: Impact of Lockdowns and COVID-19 Cases using Day-of-the-Week Fixed Effects (Percentage of people moving)

(a) Impact of a full lockdown, women-men differential

(b) Impact of a doubling of COVID-19 cases, women-men differential

(c) Impact of a full lockdown, differential with respect to 65+

(d) Impact of a doubling of COVID-19 cases, differential with respect to 65+

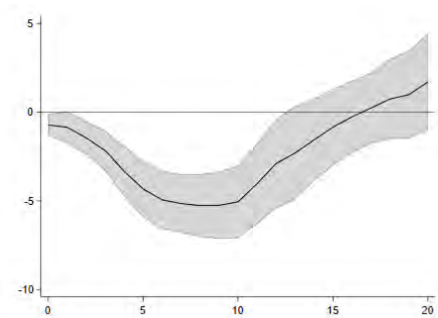


Notes: The x-axes denote the number of days, the lines denote the point estimates, and the shaded areas correspond to 90 percent confidence intervals computed with standard errors clustered at the province level.

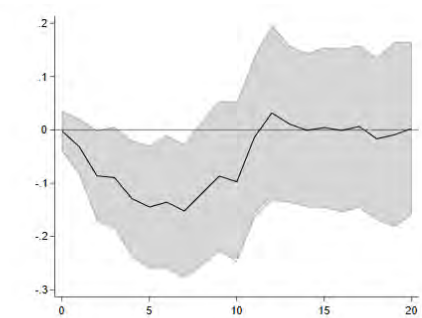
Spain. In both cases, the results closely mimic those in the baseline analysis. The only difference is that an increase in COVID-19 cases tends to have a larger impact on women's mobility relative to men's, especially when Spain is excluded in panel 13b. Yet, the point estimates are quantitatively very small.

Figure 12: Impact of Lockdowns and COVID-19 Cases Excluding Portugal
(Percentage of people moving)

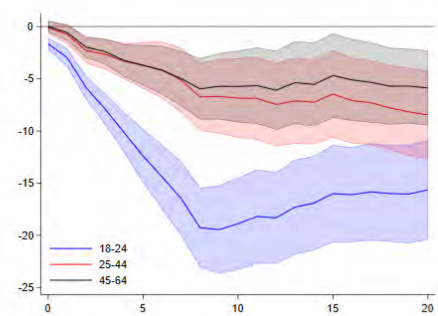
(a) Impact of a full lockdown, women-men differential



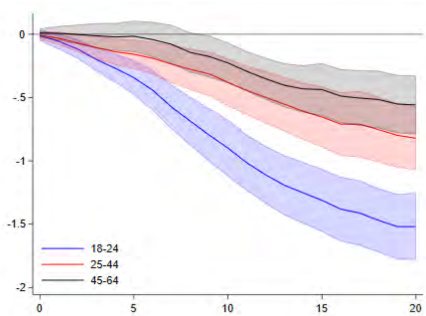
(b) Impact of a doubling of COVID-19 cases, women-men differential



(c) Impact of a full lockdown, differential with respect to 65+



(d) Impact of a doubling of COVID-19 cases, differential with respect to 65+



Notes: The x-axes denote the number of days, the lines denote the point estimates, and the shaded areas correspond to 90 percent confidence intervals computed with standard errors clustered at the province level.

As in the case of the RD analysis, we also verified that the results of the local projections are robust to applying a logistic transformation to the mobility indicator and to splitting the sample depending on province characteristics. These results are available upon request.

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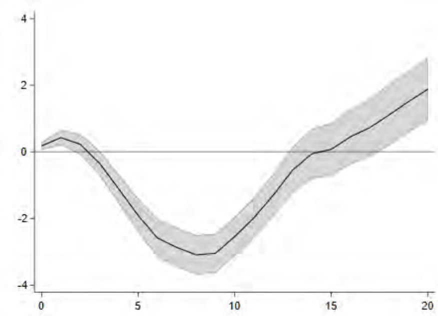
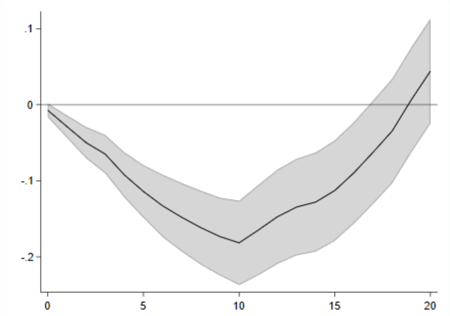
Figure 13: Impact of Lockdowns and COVID-19 Cases Excluding Spain
(Percentage of people moving)

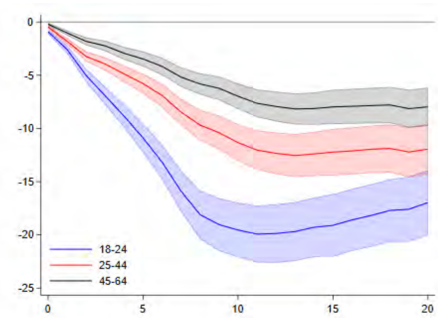
(a) Impact of a full lockdown, women-men differential



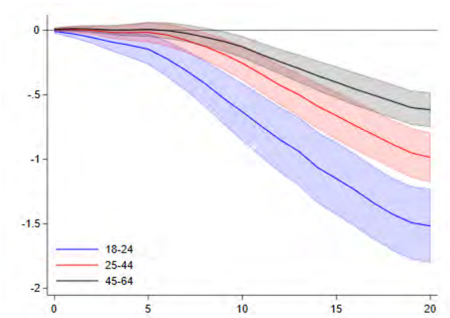
(b) Impact of a doubling of COVID-19 cases, women-men differential



(c) Impact of a full lockdown, differential with respect to 65+



(d) Impact of a doubling of COVID-19 cases, differential with respect to 65+



Notes: The x-axes denote the number of days, the lines denote the point estimates, and the shaded areas correspond to 90 percent confidence intervals computed with standard errors clustered at the province level.

7 Conclusions

We have used unique mobility indicators provided by Vodafone which differentiate by gender and age characteristics to shed light on several key themes that have emerged during the COVID-19 pandemic.

First, the analysis provides novel evidence about the disproportionate impact of the crisis on women. Lockdown measures reduce the mobility of women more than men's. This seems largely due to women carrying an uneven burden in caring for children when schools are closed. Stay-at-home orders have indeed a larger impact on women's mobility especially for those aged between 25 and 44 that are more likely to have young children. Furthermore, evidence from a few regions in Northern Italy that closed schools before adopting stay-at-home orders shows that the mobility gender gap opened already at the time of school closures. In this respect, this paper contributes to the broader literature on the determinants of labor force participation. Previous studies have found that (exogenous changes in the) length of school schedules impact female labor force participation (Berthelon et al., 2015.) Our study provides complementary high-frequency evidence.

These findings warn about a possible widening of gender inequality, as women may compromise their employment opportunities if they have to stay at home to care for children. These concerns are further heightened by the fact that women tend to be employed in contact-intensive sectors—such hospitality, personal care, and retail—that have been more severely impacted by the pandemic. Targeted policy intervention is required to support women during the pandemic, for example by offering parental leave to both men and women to encourage equal burden sharing in caring for children when schools are closed.

Second, the analysis contributes to the debate about the uneven effects of the crisis across age groups. By containing the spread of the virus, lockdowns benefit especially people above 65 years of age because they face much greater health risks from COVID-19. The economic costs of lockdowns fall instead disproportionately on working age people. The analysis shows that lockdowns lead to a stronger reduction in the mobility of younger people, for example by preventing them from reaching their work places and bringing children to school.

Interestingly, the mobility of younger people responds more strongly also to rising infections, for a given level of the stringency of lockdowns. Consistent with survey evidence, this could be because younger people are more concerned about the virus despite being less likely to develop severe health conditions. Or it may capture that rising infections reduce business activities in contact-intensive sectors, such as bars and restaurants, leaving many young people that work in those sectors unemployed.

The disproportionate impact of lockdowns on the mobility of the young is particularly concerning because young workers depend on labor income to sustain consumption while older people have access to larger personal saving and often receive stable retirement income. Younger workers also tend to have less stable job contracts that are more likely to be terminated during a crisis. These considerations highlight the need for a social pact across generations to at least partially compensate younger workers for the economic losses they face because of lockdowns. This is essential not only from a fairness standpoint but also to ensure enough public support to deploy lockdown measures when needed.

Third, the results on the differential effects on age groups provide insights on the possible long-term effects of the lockdown. The fact that younger generations reduced mobility more the older generations during the lockdown suggests that the scarring effects could be long lasting. This effect would be compounding the known effect that generations entering the labor force during a recession suffer a long-term scarring effect.

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This is a preliminary insight that should be investigated further in the future.

Fourth, the fact that different demographic groups react differently to stay-at-home orders, school closures, and COVID-19 cases can provide important inputs for the formulation of targeted policies in the context of resurgent epidemics in several regions of the world.

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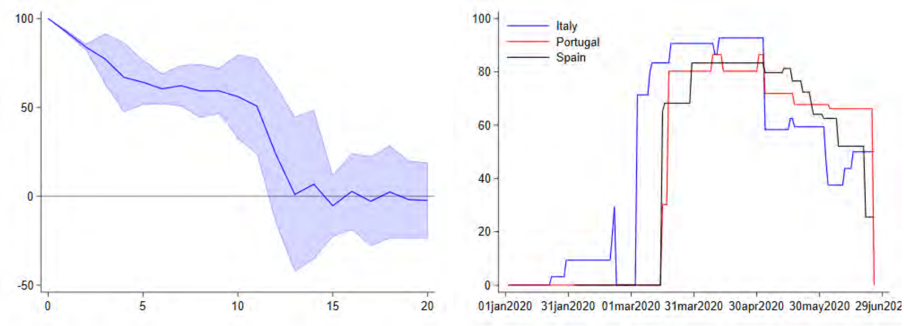
Appendix A. Lockdown stringency dynamics

To better understand the dynamics uncovered by the local projections regarding how lockdowns affect mobility, it is helpful to examine how the stringency of lockdowns evolves over the local projection horizon. Panel A.1a shows that a lockdown tightening tends to gradually decline and dissipate after about two weeks. These estimated dynamics reflect the way in which Italy, Portugal, and Spain have adjusted their lockdown stringency during the sample of analysis. As illustrated in panel A.1b, countries have adjusted the stringency of lockdowns rather frequently.

Figure A.1: Lockdown Stringency Dynamics

(a) Impact of a full lockdown on lockdown stringency (Percentage of people moving)

(b) Lockdown stringency (Index)



Notes: In panel A.1a, the x-axis denotes the number of days, the line denotes the point estimates, and the shaded area corresponds to the 90 percent confidence interval computed with standard errors clustered at the province level.

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Lockdowns and the US unemployment crisis[1]

Christian Dreger[2] and Daniel Gros[3]

Date submitted: 7 January 2021; Date accepted: 8 January 2021

We analyse the short-term impact of social distancing measures on the US labour market, using a panel threshold model with high frequency (weekly) data on unemployment across US states. We find that changes in the restrictiveness of mandated social distancing, as measured by the Oxford Stringency Index, exert a strong immediate impact on initial unemployment. The unemployment rate is not immediate affected but follows within a very short time (two to four weeks). We also document a substantial asymmetry between tightening and easing: the impact of tightening restrictions is twice as large as that of easing them. The state of the endemic, proxied either by cases or fatalities, constitutes a marginal factor.

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1 Many thanks to Alexandre Ounnas for support with the data and to CEPS colleagues for comments. This research has received funding from the Horizon 2020 research and innovation programme of the EU under grant agreement No. 101016233, H2020-SC1-PHE CORONAVIRUS-2020-2-RTD, PERISCOPE (Pan European Response to the Impacts of Covid-19 and future Pandemics and Epidemics).

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3 Centre for European Policy Studies.

1 Introduction

The Covid-19 pandemic has led to unprecedented economic decline. Since February 2020, policymakers around the globe have introduced several emergency measures such as social distancing and the wearing of masks, restrictions to mobility and travel and shutting down large parts of the economy, including firms, workplaces and schools. The aim to slow down the spread of the virus (flatten the curve) led to the harsh restrictions (lockdown). During the summer of 2020, many restrictions were lifted or relaxed, only to be reinstated when infections surged again during the autumn and winter. However, However, the lockdown has been associated with a deep economic recession. Following Barro et al. (2020), the losses in output and consumption attributed to the current virus exceed those of the Spanish flu, even under conservative assumptions.

The key question for policymakers is how to manage the trade-off between the spread of the virus and the severity of the lockdown measures. Dealing with this trade-off is a major challenge under pandemic conditions (Eichenbaum et al., 2020).

The pandemic shifted both the supply and demand curve in the economy. On the supply side, infections and lockdowns worsened labour supply and productivity. On the demand side, layoffs and income losses (because of morbidity, quarantines, and unemployment) lowered household consumption and firms' investment. For example, more than one half of participants surveyed reported substantial income and wealth losses. Large drops in consumption, especially in travel and clothing, are also involved (Coibion et al., 2020). The high uncertainty with respect to the path, duration and impact of the pandemic might create downward spirals that dampen business and consumer confidence, with further job losses due to the anticipation of lower future demand. Higher credit default and non-performing loans might contribute to tighter lending standards. Guerrieri et al. (2020) argue that supply shocks associated with the Covid-19 pandemic are amplified by changes in aggregate demand, especially shutdowns, layoffs and the exit of firms.

The appropriate design of policies is critical, as massive losses can be involved. However, empirical evidence on the impact of policies is rather scarce. Several studies have discussed the impact of non-pharmaceutical interventions (NPI) on the evolution of the pandemic, the latter measured by the growth rate of infections in OECD member states (Pozo et al., 2020) or the decline in the virus reproduction rates (Brauner et al., 2020). The interventions are found to be successful in flattening the infection curve. Hsiang et al. (2020) argue that the interventions dampened the contagion, to the order of 61 million Covid-19 cases in six major countries (China, South Korea, Italy, Iran, France, and the US).

We provide new evidence on the short run impact of social distancing measures and the state of the endemic on the labour market, using high frequency labour market data from the US.

The next section provides a summary of existing studies of the economic impact of social distancing. Section 3 presents the broad trends of the US labour market during the 'great lockdown'. Section 4 explains the index of restrictiveness used and section 5 presents the main results from our panel estimates allowing for asymmetric effects, using data for US states close to 40 weekly data observations per state. Section 6 concludes.

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2. Studies of the economic impact of social distancing

A large number of studies has already investigated the impact of the lockdown on the economy, although mostly from a model-specific angle concentrating on the early phase of the pandemic.

Bodenstein et al. (2020) stress that the absence of social distancing may amplify the costs over longer time intervals. To lower the costs in economic terms, social distancing should be skewed towards non-essential industries and professions that can be performed from home. Due to input-output linkages, however, even non-targeted industries can be affected. According to Getachev (2020), voluntary distancing is very important for both flattening the infection curve and limiting damage to the economy over the course of the endemic. Laeven (2020) emphasises that producers of intermediates tend to be more affected by the crisis if they sell le their output to industrial sectors restricted by social distancing.

Based on costly disasters from the past, Ludvigson et al. (2020) estimate the costs of the pandemic for the US. While past disasters were mostly locally concentrated and rather short-lived, the Covid-19 shock is modelled as a sequence of large disasters in a VAR environment. Even under a conservative scenario, the pandemic will lead to cumulative losses in industrial production of 20% and in employment in the services sector of 40%, i.e. more than 55 million jobs are expected to be lost over the next 12 months. Massive reallocations of labour are thus involved.

Chudik et al. (2020) specify a threshold global VAR model to quantify the potentially nonlinear macroeconomic effects of Covid-19. The relationship between output growth and uncertainty, proxied by excess volatility, is subject to threshold effects for both advanced and emerging countries. The Covid-19 shock is identified by the IMF forecast revisions of GDP growth. Results suggest that the pandemic will cause a long-lasting decline in global output, although the effects tend to be unequal in different regions. While Asian countries are less affected, and boosted by the Chinese catch-up, the impacts are greater in the West. Due to strong interlinkages through trade flows, the findings call for a coordinated multi-country policy response to mitigate the effects of the pandemic.

With respect to the labour market, the fact that the pandemic has exacerbated pre-existing inequalities has received most attention. Although employment losses have been widespread, they are substantially larger in lower-paying occupations and industries. Individuals from disadvantaged groups, i.e. Hispanics, younger workers, those with lower levels of education and women have suffered larger job losses and decreases in hiring rates (Cortes and Forsythe, 2020). This indicates that the economic burden of the corona crisis will mostly affect those people who are already in the most vulnerable financial situation (Gascon, 2020). Job losses tend to be less pronounced for employees who can work remotely (Montenovo et al., 2020). By looking at high frequency state-level data, Baek et al. (2020) argue that orders to people to stay at home unless their work is deemed essential accounted for a substantial, but minority share of the rise in unemployment claims.

Pagano et al. (2020) and Capelle-Blancard and Desroziers (2020) examine the effects of the pandemic on the US stock market and highlight its differential impact on various sectors. Baker et al. (2020) show that uncertainty proxied by stock market volatility, newspaper-based uncertainty and subjective uncertainty in busines expectation surveys rose sharply as the pandemic worsened.

Kok (2020) reports a negative relationship between GDP growth and stringency policy measures in a panel of 106 developed and developing countries. As GDP information is available only quarterly and with considerable delay, the time series dimension of such an analysis is very short. (only 2-3 observations per country). The weekly data we use has 12 times more observations per regional unit.

By using real-time information on vacancies and unemployment insurance claims, Forsythe et al. (2020) conclude that the US labour market deteriorated substantially but did so across the board, rather than more so in states with shutdown orders. Therefore, individual state policies and own epidemiological situations have had only a modest effect, see also Rojas et al. (2020). By contrast, Gupta et al. (2020) found a major role for state social-distancing policies, in addition

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to the impact of the nationwide shock. There has been a broad retreat across almost all industries, whether they are essential or not. Based on a survey of 5,800 small businesses, Bartik et al (2020) find large employment losses caused by the pandemic.

Most of the existing studies concentrate on the initial phase of the pandemic (first wave) and the ensuing harsh lockdown. Our contribution includes data until the autumn of 2020, a time period during which many restrictions were first loosened and then tightened again. Moreover, we look separately at different measures, allowing us a more precise estimate of which measures had the biggest impact.

Our analysis provides novel evidence on the impact of the lockdown on the US economy, in several respects.

First of all, our sample spans a period of substantial reversal of measures, which were eased during the summer and then re-imposed or tightened again later during the year.

Moreover, we use unemployment data per state to exploit the large differences in the path of the pandemic across US regions.

Finally, we use a high frequency, namely weekly data. Unemployment (claims and rates) seem to be the only real economy data available at this frequency.

A number of very high frequency indicators have been created recently to track output or GDP, even on a daily basis. We do not employ these indicators because we are interested in the size and speed of the impact of social-distancing measures on the labour market (rather than some synthetic measure of overall economic activity).

As 36 weeks and 51 states (including the District of Columbia) are considered, empirical evidence can be based on more than 1,800 observations.

The results point to a strong and quick impact of the lockdown on unemployment. From the variety of measures included in the Oxford index, school closures and stay-at-home regulations are most critical for the economy. The reaction of unemployment to a changing social distancing restrictions is observed with a delay of only about two to four weeks.

In addition, the evolution of unemployment is governed by substantial asymmetries. If the government switches to tighter regulations, the increase in unemployment is higher in absolute value than a decrease after a relaxation. Hence, the decline in unemployment towards the end of the sample cannot be explained in terms of regulation easing.

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Controls representing the spread of the disease, such as the number of new infections and especially the number of deaths exert some impact, but their role is minor.

3 Trends in US labour markets during the 'great lockdown'

The corona crisis led to a sudden increase in US unemployment. While the insured unemployment rate (IUR) was at record lows just before the outbreak of the crisis, it shot up to almost 16% in April. Since then, unemployment has gradually fallen, but remains at more than double the pre-crisis value.

The IUR is equal to the number of people receiving unemployment insurance as a percentage of the labour force and reported at a weekly frequency. The measured IUR does not comove immediately one to one with the number of unemployment claims filed in the same week. This was particularly the case in the early phases of the crisis when the local unemployment offices were overwhelmed by the huge number of initial claims. Figure 1 illustrates how initial unemployment claims shot up immediately when major measures were taken, followed by a more gradual increase in the (insured) unemployment rate.

Initial claims (IUC) might thus constitute a useful alternative measure of the state of the labour market (Cajner, 2020). Therefore, initial unemployment claims are also used for a robustness test.

Figure 1: Initial unemployment claims (IUC) and the Insured Unemployment Rate (IUR) during the lockdown

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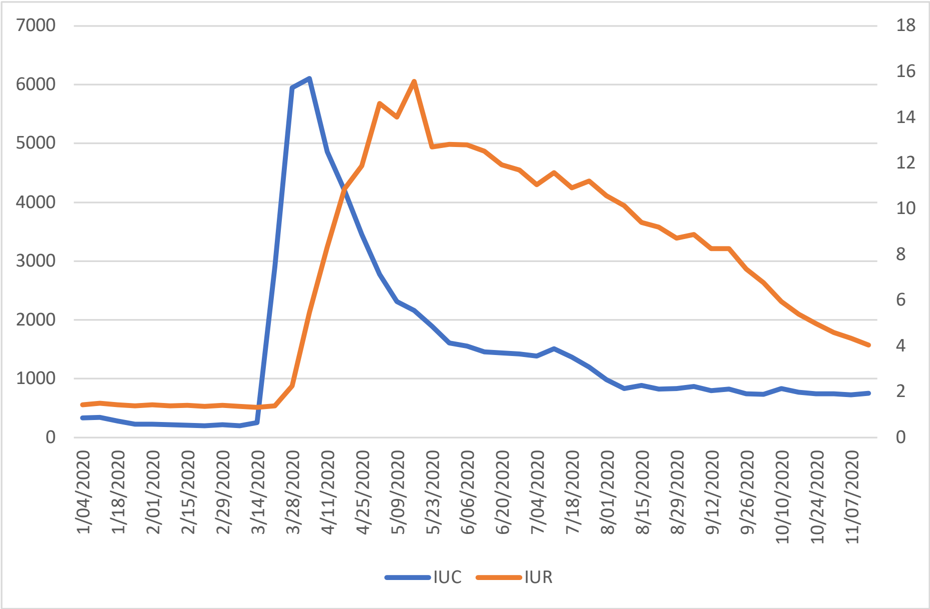

Source: Own elaborations on BLS data. Left hand axis initial unemployment claims (total for US) in thousands. Right hand axis: average insured unemployment rate.

In terms of both the IUR and IUC one finds a similar pattern throughout the US of course, marked by an initial sharp increase, followed by a gradual decline and then another uptick.

Within this overall pattern, the magnitudes differ substantially across states. For instance, the largest increase in the unemployment rate, of almost 30 percentage points, can be observed for Washington, followed by California, Vermont and Florida. In contrast, the labour markets in Utah and Wyoming showed higher resilience, with an increase of around 6 percentage points. States with a high share of employment in the tourism sector like Nevada (25%, gaming industry) and Hawaii (20%) experienced an above-average increase in unemployment but they are not those with the largest employment losses.

Figure 2: Unemployment rates across States: average and dispersion

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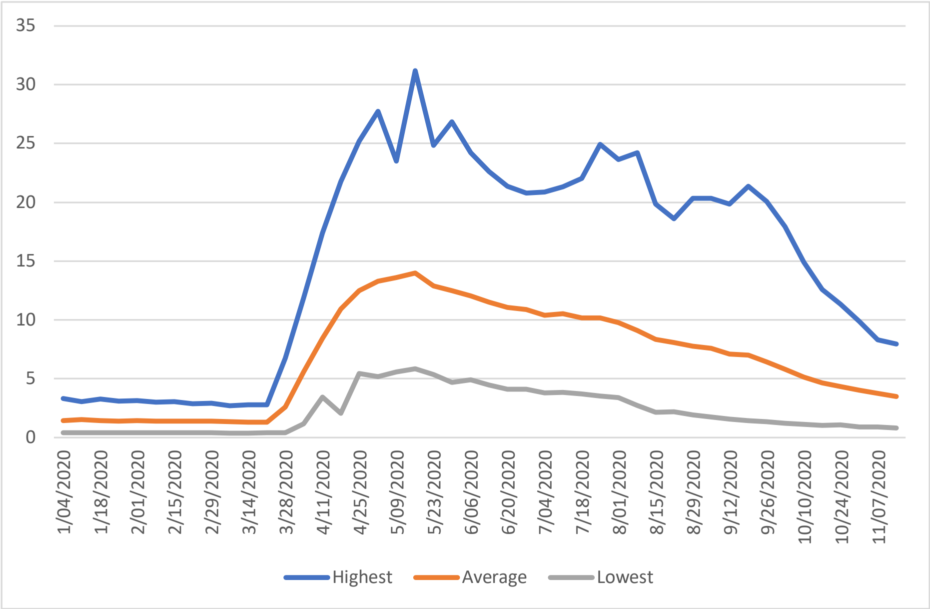

Source: Own elaborations on BLS data. The line 'Highest' shows the value for the US State with the highest value for that week and similarly for 'Lowest'.

4 Measuring policy restrictions

Several indicators are available to assess the scope of corona-related policies. The government response tracker developed by the Blavatnik School of Government, Oxford University, is the standard measure of policies to arrest the spread of the virus (Hale et al., 2020). It collects daily information on containment and closure practices, which is publicly available from various sources.[1] The components of the Oxford index are rank scaled. Larger values represent a higher level of stringency of the respective policy but quantitative differences between two values cannot be interpreted (Table 1).

[1] One alternative to the Oxford indicator is the Google mobility index. It includes several aspects of mobility behaviour, such as visits to parks. For this paper, its value is very limited, as the series are strongly affected by seasonal patterns. Compared to Feb 2020, the Google index shows an increase in mobility at the current edge, probably not because of relaxed restrictions but warmer temperatures after winter.

Table 1: Components of the Oxford indices

	Min/Max
School closures	0/3
Working place closures	0/3
Cancellation of public events	0/2
Restrictions on gatherings	0/4
Close of public transport	0/2
Stay at home requirements	0/3
Restrictions on internal movements	0/2
International travel controls	0/4

Note: Dimensions of the Oxford stringency index. Min/Max column represents minimum and maximum values. Taken the closures of schools as an example, the values are 0 (no closure), 1 (closing recommended), 2 (only some types of schools, such as high schools) and 3 (all schools).

Table 2: Correlation between Oxford components

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8
O_1	1							
O_2	0.73	1						
O_3	0.75	0.79	1					
O_4	0.73	0.76	0.80	1				
O_5	0.43	0.46	0.42	0.41	1			
O_6	0.62	0.70	0.68	0.65	0.34	1		
O_7	0.49	0.57	0.50	0.53	0.22	0.51	1	
O_8	0.27	0.24	0.22	0.25	0.13	0.25	0.41	1

Source: Own calculations based on Hale et al. (2020)

Each individual component is rescaled between 0 and 100. A composite indicator is constructed as the average of the individual components

(1) $$OX = \frac{1}{8}\sum_{i=1}^{8} O_i$$

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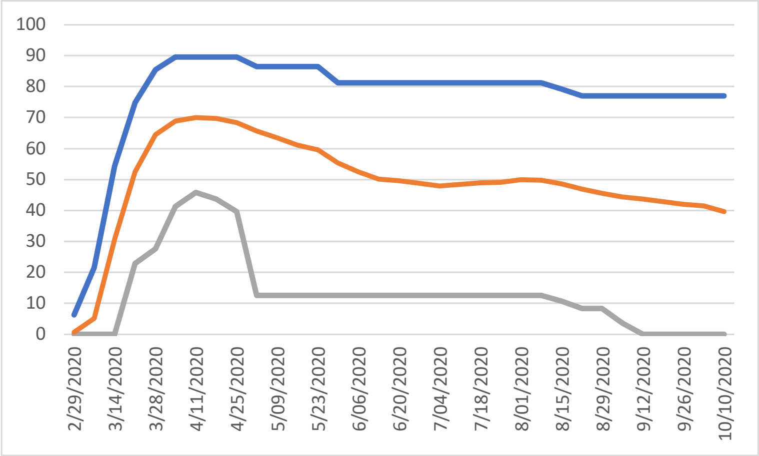
Due to their construction the indices vary between 0 and 100. In principle, the individual series in the Oxford indicator can be aggregated in different ways. The advantage of (1) is that the simple average is easy to handle and allows for some averaging out of potential measurement errors on the individual components. With the exception of international travel controls, the correlation between the other components of the Oxford indicator is rather high, where the individual coefficients often exceed 0.6, see Table 2, indicating both substantial co-movement, but also considerable differences. Despite the fact that several restrictions have been gradually lifted, the stringency of the regulations is still at rather high levels. The standard deviation of the average indicator across US states oscillates between 10 and 15 points (compared to an indicator level between 40 and 60 points). There is thus substantial cross-sectional variation that can be exploited in a panel setting.

Figure 3: Oxford stringency index for the US economy, average and dispersion



Note: Average of composite index (orange), minimum and maximum (blue and grey) across the US states.

The US federal government has only limited direct control over the implementation of strategies to combat the crisis. Instead, many decisions are taken at the state, sometimes even at the local level. The overall policy response to the virus is shown in Figure 2, together with the maximum and minimum across the US states. Measures entered into force directly after the outbreak of the crisis and reached a peak in April. Since then, a slight downward trend is observed on average. Stricter policies have been applied in Alaska, Idaho, Kentucky, Maryland and New Mexico, while Arkansas, Iowa, North and South Dakota and Utah had relatively liberal regulations. The least-stringent states, mostly in the Mid-West, had Republican governors (Hale et al., 2020).

5 Panel regressions with asymmetric effects

Panel models with state fixed effects (α) are estimated for the 51 US states (including the District of Columbia) over the pandemic period, i.e., February to mid-October 2020. Unemployment rates and initial claims are available at a weekly frequency from the BLS. Weekly Oxford indices are obtained by averaging daily values over the week. In total 51x36=1836 observations are available, implying a high number of degrees of freedom. To exclude potentially spurious regressions due to trending behaviour in the variables, the equation is expressed in first differences (Δ). As the unemployment reaction might not be immediate, a delay of up to four weeks is allowed. In addition, a threshold is introduced to capture an asymmetric unemployment response to the policy change. The slope parameters can be different, depending on whether policy is tightened or relaxed.

The spread of the virus is widely perceived to have an independent impact on the economy because news of an increase in infections can cause higher uncertainty or caution in certain consumption expenditures (restaurant trips, travel, etc.), leading to an independent fall in labour demand or a rise in unemployment (Baker et al. (2020), Coibon et al. (2020)). In order to account for this separate effect, we introduced as control both the number of infections and deaths (relative to population) at the level of the individual states.

Overall, the insured unemployment rate *u* is explained by the individual components of the Oxford indicator and the composite index aggregate (and later individual components of the) Oxford indicator *O* and corona-related controls for the spread of the disease i.e., resulting in the following equation:

$$(2) \qquad \Delta u_{it} = \alpha_{i,j} + \sum_{k=0}^{4} \beta_{j,k} \Delta O_{i,j,t-k} + \sum_{k=0}^{4} \gamma_{j,k} d_{i,j,t-k} \Delta O_{i,j,t-k} \sum_{k=0}^{4} \delta_{l,k} \Delta corona_{i,l,t-k} + \varepsilon_{i,j,t}$$

The indices *i* and *j* denote the individual state and the number of the Oxford indicator (i=1...51; j=1...8 and 9 for the composite index), *t* is time, *k* the delay and ϵ the error term. The threshold

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is implemented through a binary variable *d*. It is equal to 1 if a policy becomes tighter and 0 otherwise. Hence, the impact is equal to $\beta_{jk}+\gamma_{jk}$ if the policy *j* became stricter *k* periods ago. In case of no change or a policy relaxation, the coefficient is β_{jk}. Corona controls (*l*=1,2) refer to the number of infections and deaths associated with the pandemic. The results are shown in Table 3. To improve the readability of the results, only significant coefficients are shown. The starting point of the model evaluation is an over-parameterised structure with many insignificant variables, for instance due to multicollinearity. At each round of the subsequent iteration process, the least significant regressor is removed. The final specification includes only explanatories with *t*-values larger than 2.

Exactly the same equation is estimated using the same procedure with initial unemployment claims as the dependent variable. The two panels of Table 3 contain the results:

Table 3: Impact of NPIs on the labour market: Composite Oxford indicator

Panel a: Impact on insured unemployment rate

$$\Delta u_{it} = -\underset{(0.004)}{0.211} + \underset{(0.005)}{0.013}\Delta O_{t-1} + \underset{(0.006)}{0.032}\Delta O_{t-2} + \underset{(0.007)}{0.055}d_{t-3}\Delta O_{t-3} + \underset{(0.006)}{0.065}d_{t-4}\Delta O_{t-4}$$

$$+\underset{(0.005)}{0.013}\Delta dea_t - \underset{(0.010)}{0.027}\Delta dea_{t-1} + \underset{(0.010)}{0.030}\Delta dea_{t-2} - \underset{(0.005)}{0.015}\Delta dea_{t-3}$$

$$R2 = 0.264, \quad SER = 1.378$$

Panel b: Impact on initial unemployment claims

$$\Delta iuc_{it} = -\underset{(0.011)}{0.062} + \underset{(0.002)}{0.015}d_t\Delta O_t + \underset{(0.002)}{0.056}d_{1,t-1}\Delta O_{1,t-1} - \underset{(0.002)}{0.020}d_{1,t-2}\Delta O_{1,t-2}$$

$$-\underset{(0.001)}{0.005}d_{1,t-4}\Delta O_{1,t-4} + \underset{(0.00005)}{0.0002}\,\Delta\, inf - \underset{(0.00005)}{0.0002}\,\Delta\, inf_{t-1}$$

$$R2 = 0.527, \quad SER = 0.352$$

Note: Panel model with fixed effects for the 51 US states (including District of Columbia), weekly data from Feb 22 to Oct 10. IUC=Initial unemployment claims (logs). Standard errors in parentheses below regression coefficients. The constant is the average of state level fixed effects. *O* denotes the specific policy covered by the Oxford index, *d* is equal to 1 if a policy is tightened and 0 otherwise, *inf* is the number of new infections and *dea* the number of deaths. *R*2 adjusted coefficient of determination and *SER* the standard error of regression.

The results point to a clear impact of the lockdown on the course of unemployment, which is rapid and asymmetric.

In the case of the unemployment rate (panel a of table 3) the impact of a change in the Oxford restrictiveness indicator can be observed already after one week. If the policy is tightened (i.e. when the dummy d=1) impact continues until lag 4. The sum of the point estimates not involving a tightening is equal to 0.045, which would imply that a change in the aggregate Oxford index of one standard deviation (20 points) should be followed by a change in the unemployment rate of about 0.9 percentage point. However, the sum of the coefficients on tightening is equal to 0.11, implying that a tightening of the same amount leads to an increase in unemployment which is more than twice as large (2.2 percentage points of an increase in the Oxford Stringency Index of one standard deviation. If one considers the initial jump from zero to 70 (the average degree of restrictiveness in March) the equation could explain an increase of close to 8 points (7.7 to be precise) which is not far from the increase in the average unemployment rate recorded in Spring of 2020.

The results with initial unemployment claims as the dependent variable (panel b of table 3) show an immediate impact of the restrictions and a complete asymmetry in the sense that one finds significant coefficients only for tightening, not for a loosening of restrictions. The point estimates that the very strong immediate response is followed with one lag by a further increase in claims, which then is partially reversed during the following few weeks. Increases in infections also have a significant contemporaneous impact on unemployment claims, but it is fully compensated one period later.

The different lag structures found for the unemployment rate and initial claims is due to the more gradual increase in the unemployment rate already documented in Figure 1. This also explains why infections seem to matter more for initial claims and deaths, which are a lagging indicator) for the unemployment rate. A further difference between the results for the unemployment rate and initial claims is that explanatory power is twice as high for the latter.

The impact of controls such as the number of new infections and the number of deaths has some impact, but any effect dissipates quickly as the sum of the coefficients over all significant lags is zero.

Furthermore, we also estimated the same equation separately for each Oxford component listed in Table 1. The results are reported in table 4 in the annex.

This strategy can provide some evidence on the appropriate design of policies from an economic point of view. Table 4 in the annex shows that school closures and stay-at-home regulations are most critical for the economy. In addition, the results also confirm in all cases that the impact on unemployment is governed by substantial asymmetries. If the government switches to tighter regulations, the increase in unemployment is higher in absolute value than a decrease after a relaxation.

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These results for individual social distancing restrictions also confirm that the state of the pandemic has only a marginal impact, whether one adds as controls the number of new infections or the number of deaths. The short time lags are also confirmed. As a rule, the reaction of unemployment to a changing economic environment is observed with a delay of about two to four weeks.

6 Conclusions

The Covid-19 pandemic led to an unprecedented recession and spike in unemployment as policy makers had to resort to lockdowns to limit the spread of the disease.

This paper provides evidence on the impact of the lockdowns on labour markets in the US. We document considerable heterogeneity among individual states, both in terms of the labour market performance and the time path of the restrictions imposed.

We used panel threshold models specified for US states and based on weekly data. Two labour market indicators are used, namely the insured unemployment rate (IUR) and initial jobless claims (IJC). The details policy responses to the pandemic are proxied by the different components of the Oxford stringency index. Again, these individual indicators (e.g. school closures, prohibitions on mass gatherings, etc.) shows considerable variation across the US.

We find an impact of the policy measures on the labour market, which is strong, rapid and asymmetric.

The impact is rapid: the unemployment rate increases within 2-4 weeks of policy measures being taken and unemployment claims respond almost immediately.

The impact is asymmetric: tightening measures has an impact that is about 50% greater than that of easing measures.

The overall ‘Oxford Stringency Indicator’, an average of eight different policy intervention types, has the strongest impact on labour markets. Applying the same methodology using its individual components show that the results are very robust, and that school closures and stay-at-home regulations are the most critical for the labour market.

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Annex:

Table 4: Impact of different NPIs on the labour market

a) insured unemployment rate

School closures

$$\Delta u_{it} = -\underset{(0.038)}{0.135} + \underset{(0.003)}{0.021}\Delta O_{1,t-2} + \underset{(0.003)}{0.033}d_{1,t-3}\Delta O_{1,t-3} + \underset{(0.003)}{0.037}d_{1,t-4}\Delta O_{1,t-4}$$
$$+\underset{(0.005)}{0.014}\Delta dea - \underset{(0.010)}{0.031}\Delta dea_{t-1} + \underset{(0.010)}{0.036}\Delta dea_{t-2} - \underset{(0.005)}{0.018}\Delta dea_{t-3}$$
$$R2 = 0.221, \quad SER = 1.417$$

Working place closures

$$\Delta u_{it} = -\underset{(0.036)}{0.205} + \underset{(0.003)}{0.008}\Delta O_{2,t} + \underset{(0.004)}{0.036}d_{2,t-2}\Delta O_{1,t-2} + \underset{(0.004)}{0.025}d_{2,t-3}\Delta O_{2,t-3}$$
$$+\underset{(0.004)}{0.045}d_{2,t-4}\Delta O_{2,t-4}$$
$$R2 = 0.222, \quad SER = 1.418$$

Cancellation of public events

$$\Delta u_{it} = -\underset{(0.039)}{0.181} + \underset{(0.002)}{0.005}\Delta O_{3,t-1} + \underset{(0.003)}{0.016}d_{3,t-2}\Delta O_{3,t-2} + \underset{(0.003)}{0.027}d_{3,t-3}\Delta O_{3,t-3}$$
$$+\underset{(0.003)}{0.040}d_{3,t-4}\Delta O_{3,t-4} + \underset{(0.005)}{0.014}\Delta dea - \underset{(0.010)}{0.025}\Delta dea_{t-1} + \underset{(0.010)}{0.034}\Delta dea_{t-2} - \underset{(0.005)}{0.020}\Delta dea_{t-3}$$
$$R2 = 0.198, \quad SER = 1.438$$

Restrictions on gatherings

$$\Delta u_{it} = -\underset{(0.039)}{0.206} + \underset{(0.003)}{0.007}\Delta O_{4,t-1} + \underset{(0.003)}{0.025}d_{4,t-2}\Delta O_{4,t-2} + \underset{(0.003)}{0.028}d_{4,t-3}\Delta O_{4,t-3}$$
$$+\underset{(0.003)}{0.036}d_{4,t-4}\Delta O_{4,t-4} + \underset{(0.005)}{0.017}\Delta dea_t - \underset{(0.010)}{0.026}\Delta dea_{t-1} + \underset{(0.010)}{0.031}\Delta dea_{t-2} - \underset{(0.005)}{0.018}\Delta dea_{t-3}$$
$$R2 = 0.214, \quad SER = 1.424$$

Close of public transport

$$\Delta u_{it} = -\underset{(0.041)}{0.073} + \underset{(0.004)}{0.011}\Delta O_{5,t} + \underset{(0.006)}{0.029}d_{5,t-1}\Delta O_{5,t-1} + \underset{(0.006)}{0.032}d_{5,t-2}\Delta O_{5,t-2}$$
$$+ \underset{(0.006)}{0.042}d_{5,t-3}\Delta O_{5,t-3}$$

$$+\underset{(0.006)}{0.030}d_{5,t-4}\Delta O_{5,t-4} + \underset{(0.006)}{0.013}\Delta dea_t - \underset{(0.011)}{0.027}\Delta dea_{t-1} + \underset{(0.011)}{0.032}\Delta dea_{t-2} - \underset{(0.006)}{0.018}\Delta dea_{t-3}$$

$$R2 = 0.106, \quad SER = 1.518$$

Stay-at-home requirements

$$\Delta u_{it} = -\underset{(0.039)}{0.208} + \underset{(0.006)}{0.020}\Delta O_{6,t-2} + \underset{(0.005)}{0.039}d_{6,t-1}\Delta O_{6,t-1} + \underset{(0.008)}{0.021}d_{6,t-2}\Delta O_{6,t-2}$$

$$+ \underset{(0.005)}{0.040}d_{6,t-3}\Delta O_{6,t-3}$$

$$+\underset{(0.005)}{0.052}d_{6,t-4}\Delta O_{6,t-4} + \underset{(0.005)}{0.017}\Delta dea_t - \underset{(0.010)}{0.026}\Delta dea_{t-1} + \underset{(0.010)}{0.030}\Delta dea_{t-2} - \underset{(0.005)}{0.017}\Delta dea_{t-3}$$

$$R2 = 0.239, \quad SER = 1.401$$

Restrictions on internal movement

$$\Delta u_{it} = -\underset{(0.041)}{0.125} + \underset{(0.003)}{0.010}\Delta O_{7,t} + \underset{(0.004)}{0.019}d_{7,t-1}\Delta O_{7,t-1} + \underset{(0.004)}{0.028}d_{7,t-2}\Delta O_{7,t-2}$$

$$+ \underset{(0.004)}{0.026}d_{6,t-3}\Delta O_{7,t-3}$$

$$+\underset{(0.003)}{0.024}d_{7,t-4}\Delta O_{7,t-4} + \underset{(0.006)}{0.021}\Delta dea_t - \underset{(0.011)}{0.032}\Delta dea_{t-1} + \underset{(0.011)}{0.026}\Delta dea_{t-2} - \underset{(0.006)}{0.016}\Delta dea_{t-3}$$

$$R2 = 0.133, \quad SER = 1.495$$

International travel controls

$$\Delta u_{it} = \underset{(0.042)}{0.035} + \underset{(0.010)}{0.036}d_{8,t-1}\Delta O_{8,t-1} + \underset{(0.010)}{0.043}d_{8,t-3}\Delta O_{8,t-3} + \underset{(0.010)}{0.025}d_{8,t-4}\Delta O_{8,t-4}$$

$$+\underset{(0.006)}{0.027}\Delta dea - \underset{(0.011)}{0.038}\Delta dea_{t-1} + \underset{(0.011)}{0.034}\Delta dea_{t-2} - \underset{(0.006)}{0.023}\Delta dea_{t-3}$$

$$R2 = 0.019, \quad SER = 1.591$$

Note: Panel model with fixed effects for the 51 US states (including District of Columbia), weekly data from Feb 22 to Oct 10. Standard errors in parentheses below regression coefficients. The constant is the average of state level fixed effects. *O* denotes the specific policy covered by the Oxford index, *d* is equal to 1 if a policy is tightened and 0 otherwise, *inf* is the number of new infections and *dea* the number of deaths. *R*2 adjusted coefficient of determination and *SER* the standard error of regression.

Table 4 continued,

b) initial unemployment claims

School closures

$$\Delta iuc_{it} = \underset{(0.010)}{-0.067} - \underset{(0.001)}{0.003}\Delta O_{1,t-4} + \underset{(0.001)}{0.009}d_{1,t}\Delta O_{1,t} + \underset{(0.001)}{0.029}d_{1,t-1}\Delta O_{1,t-1}$$
$$+\underset{(0.00005)}{0.0001}\Delta\, inf - \underset{(0.00005)}{0.0001}\Delta\, inf_{t-1}$$
$$R2 = 0.572, \quad SER = 0.335$$

Working place closures

$$\Delta iuc_{it} = \underset{(0.012)}{-0.048} + \underset{(0.001)}{0.015}d_{2,t}\Delta O_{2,t} + \underset{(0.001)}{0.021}d_{2,t-1}\Delta O_{2,t-1} - \underset{(0.001)}{0.003}d_{2,t-3}\Delta O_{2,t-3}$$
$$-\underset{(0.001)}{0.003}d_{2,t-4}\Delta O_{2,t-4} + \underset{(0.00005)}{0.0001}\Delta\, inf_t - \underset{(0.00005)}{0.0001}\Delta\, inf_{t-1}$$
$$R2 = 0.380, \quad SER = 0.404$$

Cancellation of public events

$$\Delta iuc_{it} = \underset{(0.012)}{-0.058} + \underset{(0.001)}{0.036}d_{3,t}\Delta O_{3,t} + \underset{(0.001)}{0.025}d_{3,t-1}\Delta O_{3,t-1} + \underset{(0.001)}{0.004}d_{3,t-2}\Delta O_{3,t-2}$$
$$-\underset{(0.001)}{0.003}d_{3,t-4}\Delta O_{3,t-4} + \underset{(0.00005)}{0.0003}\Delta\, inf - \underset{(0.00005)}{0.0003}\Delta\, inf_{t-1}$$
$$R2 = 0.443, \quad SER = 0.382$$

Restrictions on gatherings

$$\Delta iuc_{it} = \underset{(0.012)}{-0.053} + \underset{(0.001)}{0.003}\Delta O_{4,t-1} + \underset{(0.001)}{0.013}d_{4,t}\Delta O_{4,t} + \underset{(0.001)}{0.021}d_{4,t-1}\Delta O_{4,t-1}$$
$$-\underset{(0.002)}{0.005}d_{4,t-4}\Delta O_{4,t-4} + \underset{(0.001)}{0.0002}\Delta\, inf_t - \underset{(0.001)}{0.0003}\Delta\, inf_{t-1}$$
$$R2 = 0.408, \quad SER = 0.394$$

Close of public transport

$$\Delta iuc_{it} = \underset{(0.013)}{0.016} + \underset{(0.002)}{0.021}d_{5,t}\Delta O_{5,t} + \underset{(0.002)}{0.012}d_{5,t-1}\Delta O_{5,t-1} - \underset{(0.002)}{0.004}d_{5,t-3}\Delta O_{5,t-3}$$
$$+\underset{(0.00001)}{0.0002}\Delta\, inf_t - \underset{(0.00001)}{0.0003}\Delta\, inf_{t-1}$$
$$R2 = 0.118, \quad SER = 0.474$$

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Stay-at-home requirements

$$\Delta iuc_{it} = -\underset{(0.012)}{0.007} + \underset{(0.001)}{0.006}\Delta O_{6,t-1} + \underset{(0.001)}{0.031} d_{6,t}\Delta O_{6,t} - \underset{(0.001)}{0.004} d_{6,t-3}\Delta O_{6,t-3}$$
$$+\underset{(0.00001)}{0.0003}\Delta\, inf_t - \underset{(0.00001)}{0.0003}\Delta\, inf_{t-1}$$
$$R2 = 0.254, \quad SER = 0.436$$

Restrictions on internal movement

$$\Delta iuc_{it} = \underset{(0.014)}{0.027} + \underset{(0.001)}{0.012} d_{7,t}\Delta O_{7,t} + \underset{(0.001)}{0.005} d_{7,t-1}\Delta O_{7,t-1} - \underset{(0.001)}{0.003} d_{7,t-4}\Delta O_{7,t-4}$$
$$+\underset{(0.00001)}{0.0003}\Delta\, inf_t - \underset{(0.00001)}{0.0003}\Delta\, inf_{t-1}$$
$$R2 = 0.085, \quad SER = 0.489$$

International travel controls

$$\Delta iuc_{it} = \underset{(0.014)}{0.060} + \underset{(0.003)}{0.012} d_{8,t-1}\Delta O_{8,t-1} - \underset{(0.003)}{0.008} d_{8,t-4}\Delta O_{8,t-4}$$
$$+\underset{0.00001}{0.0003}\Delta\, inf_t - \underset{(0.00001)}{0.0004}\Delta\, inf_{t-1}$$
$$R2 = 0.006, \quad SER = 0.510$$

Note: Panel model with fixed effects for the 51 US states (including District of Columbia), weekly data from Feb 22 to Oct 10. IUC=Initial unemployment claims (logs). Standard errors in parentheses below regression coefficients. The constant is the average of state level fixed effects. *O* denotes the specific policy covered by the Oxford index, *d* is equal to 1 if a policy is tightened and 0 otherwise, *inf* is the number of new infections and *dea* the number of deaths. *R*2 adjusted coefficient of determination and *SER* the standard error of regression.

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A literature review on the impact of increased unemployment insurance benefits and stimulus checks in the United States[1]

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This paper is meant to present an overview of what economists have analyzed regarding the implications of two of the main components of the Coronavirus Aid, Relief, and Economic Security (CARES) Act that impact individuals: the increased UI benefits and the stimulus checks. We present the findings from the literature on these two policies implemented in the United States with an eye on potential future governmental interventions.

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1 The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff, he Board of Governors, or the Federal Reserve System.

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Introduction

Congress passed the first COVID-19 relief package for businesses and individuals in March, when the Coronavirus Aid, Relief and Economic Security (CARES) Act came to life, which provided, among other things, one-time stimulus checks for individuals, extended unemployment insurance (UI) benefits, relief for state and local governments, liability protection, and the Paycheck Protection Program for small-business loan forgiveness.

The COVID-19 pandemic has kept economists busy analyzing every possible economic side of the coronavirus impact. This paper is meant to present an overview of what economists have analyzed regarding the implications of two of the main components of the CARES Act that impact individuals: the increased UI benefits and the stimulus checks. We present the findings from the literature on these two policies with an eye on potential future governmental interventions. Taken together, these two components alone have been effective at providing stimulus and lowering poverty. Kaplan et al. (2020) find that the initial UI benefits and stimulus payments boosted aggregate consumption by two percentage points, while Bayer et al. (2020) show that the CARES transfers reduced the output loss due to the pandemic by up to 5 percentage points. By summarizing the impact of these two provisions of the CARES Act, we hope that this paper will inform readers on the potential impact of similar provisions in the next stimulus bill. Importantly, this paper will not focus on the large COVID-19 literature that discusses health impacts, distancing measures, epidemiological models, pandemic-induced mortality changes, or the impact of other policies, domestic or foreign. For a more general review of these other topics, please refer to Brodeur et al. (2020.)

Unemployment Insurance Benefits

CARES provisions. The CARES Act provisions prescribe an additional 13 weeks of federally-funded benefits under the new Pandemic Emergency Unemployment Compensation (PEUC) program in addition to the standard state-administered UI programs for those currently receiving

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UI benefits and new applicants. These benefits were then extended for another 13 weeks (and potentially for another seven following those) through the Extended Benefits program. Normal benefits included an additional $600 per week for up to four months, which is a provision that expired on July 31st, 2020. On August 8th, a reduced weekly check of $300 was reinstated for an additional six weeks subject to state application. All states but South Dakota applied for it. Finally, there is also a new program, the Pandemic Unemployment Assistance (PUA,) for individuals who are self-employed, seeking part-time employment, or who otherwise would not qualify for regular UI benefits. The PUA program provides up to 39 weeks of benefit. Importantly, the CARES Act also required states to relax the criterion of actively searching for work to qualify for these benefits to account for illness, quarantine, and movement restrictions.

Impact of COVID-19 on unemployment. The COVID-19 pandemic has impacted employment greatly, especially for lower-pay and nonessential occupations, as shown in Liu and Mai (2020.) Over March and April 2020, job losses were larger for these occupations, especially for those with higher physical proximity or lower work-from-home feasibility. Between April and June 2020, the industries that were hit harder also recouped more jobs, but the recovery was far from full. Chetty et al. (2020a) show that high-wage workers experienced a recession that lasted a few weeks, and are now facing an almost-back-to-normal market, and they rarely lost jobs, whereas many low-wage workers lost their job because of the pandemic and had to experience a recession that would last for several months, with a job market that is still far from normal. Forsythe et al. (2020a) show that nearly all industries and occupations saw contraction in postings and spikes in UI claims, with essential jobs taking the smallest hit and leisure and hospitality services the biggest hit. The pandemic-induced increase in unemployment led to the largest rise in UI claims in U.S. history (see, i.a., Cajner et al. 2020, Chetty et al. 2020b, Goldsmith-Pinkham and Sojourner 2020, and Kong and Prinz 2020 for indicators of labor-market changes during this period.) These patterns in the data suggest that an extension of the UI benefits set to expire at the end of 2020 and an extension of the already-expired increased UI benefits are a key component of any potential stimulus bill.

Effectiveness of UI benefits and difficulty to reach the most marginalized. The effectiveness of the UI benefits has been well-documented. Faria-e-Castro (2020) finds that UI benefits are successful at stimulating consumption, leading to an increase in GDP. Han et al. (2020) show that UI benefits, their expansion, and the stimulus checks led to a decline in poverty during the pandemic, which would have risen in the absence of these programs. Cortes and Forsythe (2020) show that 49 percent of the UI and CARES benefits went to workers who were in the bottom-third of the earnings distribution before the pandemic happened, which reversed the increase in labor-earnings inequality that followed the beginning of the pandemic because of the concentration of job losses among low-paying jobs. Montenovo et al. (2020) document the disparities in job losses by occupation and relate the pre-pandemic sorting by gender, race, and ethnicity into different occupations and industries to the gaps in unemployment across these categories. Bhutta et al. (2020) use detailed data from the Survey of Consumer Finances to estimate that an additional 38 percent typical working families would be able to cover six months of expenses after an unexpected income disruption, such as a job loss, under the increased UI benefits implemented with the CARES Act compared to the standard UI benefits alone. The immediate effectiveness of UI benefits to meet basic needs is also documented by Karpman and Acs (2020) and Giannarelli et al. (2020,) both of which also discuss the difficulty to reach the poorest part of the population. Delays in payment of UI benefits, also due to an overwhelmed system, are also documented in Bitler et al. (2020.) Parolin et al. (2020) also provide evidence for the challenges involved with reaching the most-marginalized parts of the population and they argue for the need of an expansion of UI benefits to contain poverty. In particular, they show that minorities were hit particularly hard by the pandemic and that the expiration of the CARES Act benefits led to an increase in poverty which was even higher than pre-pandemic levels. Bell et al. (2020) find that in California alone, communities of concentrated poverty and with a higher share of racial and/or ethnic minorities have received UI benefits at such a lower rate than wealthier, whiter communities that the number of regular UI beneficiaries would have been 23 percent higher if the rate of receipt of UI benefits across the two types of communities had been equalized. Since it was particularly difficult to reach the individuals in the population who would benefit the most from these programs, this evidence is suggestive of a need for even-greater outreach from the government to the most-marginalized parts of the U.S. population.

Temporary vs. permanent layoffs. While UI benefits have been generally effective, a separate strand of this literature analyzes the difference in impact between unemployment types: those who are on temporary layoffs and those who are permanent job losers. The individuals on temporary layoffs are those who are only unemployed on a temporary basis because they lost their job because of the lockdown but they expect their unemployment to end as soon as the lockdown ends. The individuals who are permanent job losers are those who lost their job but who do not expect to resume their job as soon as the lockdown is over. Barrero et al. (2020) estimate that 42 percent of pandemic-induced layoffs will result in permanent job loss. Carroll et al. (2020) use a consumer model in which individuals are part of three possible employment categories (employment, temporary layoff, permanent job loss) and then estimate the impact of the increased unemployment insurance benefits (as well as the stimulus checks) on consumer spending for consumers of each of these categories. They note that spending would be lower even without unemployment shocks because restrictive measures to contain the pandemic, such as lockdowns, led to the limited access of goods and services, therefore limiting spending opportunities. The employed, by definition, do not receive any UI benefits. Those individuals who are on temporary layoffs particularly benefit from the CARES Act provisions, which provide them with the means to smooth their consumption throughout their transitory shocks. Their spending recovers fully within a year. For those individuals who are permanent job losers, the authors estimate that regular consumption spending takes three years to recover on average. The impact of UI benefits is high, but the permanent job losers would particularly benefit from an expansion of UI benefits if the lockdown was extended, as their unemployment shock is always longer than the length of the lockdown itself. Because the increased UI benefits have already expired, but at the same time employment has not yet come back to normal and further restrictions are being put into place, we can interpret these results to mean that the permanent job losers would benefit from an extension of the UI benefits as long as restrictions are in place because their unemployment will be long-lasting even following the end of pandemic-induced restrictions. Gregory et al. (2020) also differentiate between those on temporary layoffs and those who are permanent job losers and find that the lockdown disproportionately disrupts the latter group, because it takes a much-longer period of time for them to find a new job. The difference between a temporary pandemic-induced unemployment and a more permanent job loss is important to inform policy, as discussed in Gallant et al. (2020) and in Forsythe et al. (2020b,) who suggest that policies designed to prop up labor demand would be successful.

Generosity of UI benefits and return-to-work decisions. The effectiveness of the UI benefits is also due to their generosity: as reported by Ganong et al. (2020,) this leads to a median replacement rate (the level of total UI benefits divided by the pre-unemployment wage) of 134 percent. They find that around two-thirds of workers have a replacement rate greater than 100 percent (as in, they receive higher benefits than the wage they used to receive.) This generosity has spurred a lot of discussion on whether such high benefits would reduce workers' willingness to go back to work because they suddenly make more than their previous wage (see, for example, Barrero et al. 2020.) Both Petrosky-Nadeau (2020) and Boar and Mongey (2020) show that this is not the case because the UI benefits are too small and too short-lived to make it worth it for individuals to give up a return-to-work offer. Their findings are confirmed by data evidence showing that return-to-work and employment rates were not lower in states where the UI benefit expansion was larger (see Altonji et al. 2020, Bartik et al. 2020, Dube 2020, and Marinescu et al. 2020.) In the very short-term, Fang et al. (2020) find that expanded UI benefits would lead to higher unemployment in the second half of the year, with larger effects with higher benefits, but that the policy would still enhance well-being for the population as a whole.

Optimality of UI benefits. The studies discussed so far analyzed the effectiveness of UI benefits and their impact on return-to-work offers, but they did not focus on whether the policy intervention was optimal. Theoretically, Guerrieri et al. (2020) show that abundant social insurance is a key ingredient of an optimal policy response in a pandemic (together with a loosening of monetary policy,) where such a policy would reallocate income from workers in sectors that are not particularly affected by the pandemic to workers in sectors that are particularly hit by the pandemic. Bredemeier et al. (2020) provide evidence for this result quantitatively. Mitman and Rabinovich (2020) find that the $600/week-policy was close to optimal and that UI benefits should be optimally increased at the start of the crisis but then lowered as the economy reopens to align incentives to return to work. Nevertheless, coupling extended UI benefits with a re-employment bonus would be an even-better option as individuals would receive much-needed help while maintaining all incentives to search for a job. It is worth noting that the previously-discussed studies both empirically and quantitatively show that return-to-work rates were not significantly affected by increased UI benefits, therefore indicating that this disruption was likely minimal. Birinci et al. (2020) find that the optimal policy would bundle UI benefits with payroll subsidies.

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Kapička and Rubert (2020) analyze the optimal policy by including virus transmission and by examining what the optimal labor-market policy would be to save lives and find that it would have been optimal to shut down businesses, impose a quarantine several weeks before the pandemic peak, and move a quarter of workers out of employment to limit transmission.

Stimulus Checks

CARES provisions. The CARES Act provision prescribes a direct cash payment of $1,200 for each adult with an annual income of $75,000 or less plus $500 for each child. For incomes higher than $75,000, the benefit begins to phase out and is nil for any income at or above $99,000.

Impact of stimulus checks on spending. Carroll et al. (2020) use their model to also estimate the impact of the stimulus checks on consumer spending for consumers in each of the three employment categories: those who are employed, those who are on temporary layoffs, and those who are permanent job losers. The employed are the ones that suffer the least, save a good part of the stimulus check upon receipt, but their spending rebounds immediately as soon as the lockdown ends. The lack of spending choices available during the lockdown induces the saving, while spending rebounds once those choices become available again due to those individuals' healthy finances. For the other two groups, i.e. both for the individuals on temporary layoffs who expect to resume their job once the lockdown ends and for the individuals who are permanent job losers who do not expect to resume their job, the unemployment insurance benefits provide a much-bigger impact on their spending because of the larger per-individual amount. For those individuals who are permanent job losers in particular, the impact of the checks on immediate consumption is quite small because they know they will need to smooth that check over a longer period of time. For the employed, whose impact on spending is only due to the stimulus checks, the authors find that, even without a lockdown, only about 20 percent of the stimulus amount would be spent immediately. The fact that only 20 percent of the checks would be spent even in the absence of any restrictive measures is indicative of the impact that the pandemic directly had on spending. This impact is also evident in household-level bank-account data, as in Bachas et al. (2020,) in weekly state-level data, as in Kobayashi et al. (2020,) and in the aggregate, as verified by the Bureau of Labor Statistics (2020) analysis in April, which showed that aggregate income rose because of the policy interventions despite the output and consumption decline caused by the restriction measures.

Optimality of stimulus checks. The previously-discussed papers take government interventions as given. The optimality of these interventions, however, is not examined. By contrast, Nygaard et al. (2020) analyze what would be the (constrained-)optimal allocation of the stimulus checks under information that can be observed by the government through the individuals' tax returns, such as the individuals' marital status, age, income, or number of children. To derive the optimal allocation of stimulus checks, they first use a life-cycle consumption-savings model with heterogeneous consumers to predict the consumption responses to $100 increments of cash transfers by age, income, marital status, and number of children. They then compare all feasible allocations of the stimulus checks across households to examine whether the government could both spend less and achieve more stimulus than what was accomplished under the CARES Act, and derive the allocation that leads to the highest stimulus effect. They find that the poor and the young, especially those with children, should have received a larger check, which is an allocation that would have allowed for the same stimulus effect at half the cost of the actual allocation. Nygaard et al. (2020) further study the optimal allocation of a second round of stimulus checks. They find that the first round of checks was not large enough. Consequently, the optimal second-round policy is similar to the optimal first-round policy: money should be allocated to the young and to poor households with children. Their findings also suggest that a stricter income requirement would lead to a larger stimulus effect.

Empirical analysis of spending patterns following stimulus. A separate strand of this growing literature uses large administrative datasets, such as transaction records, or large-scale surveys (such as Wozniak et al. 2020, among others,) to measure how consumption changed following the pandemic. Bhutta et al. (2020) estimate that an additional two percent of typical working families would be able to cover six months of expenses after an unexpected income disruption, such as a job loss, thanks to the receipt of the stimulus check. Baker et al. (2020) find that recipients on average spent about a third of the stimulus checks within a few weeks with larger effects for poorer

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consumers. Coibion et al. (2020) find that individuals reported having spent or planned to spend around 40 percent of the total transfer on average, where the amount is higher for the unemployed, the more financially-constrained, those in larger households, less educated, and who qualified for smaller transfers. Armantier et al. (2020) find that 29 percent of all stimulus payments was used for consumption, with another 35 percent used to pay down debt and the rest saved. Chetty et al. (2020a) find that stimulus payments to low-income households had large effects on their consumption. Karger and Rajan (2020) use transaction-level data during the two weeks before and after the stimulus check to analyze the change in credit- and debit-card spending immediately following the stimulus receipt. They find that the poor spent most of their check, while those in better financial health spent 23 percent of their transfer. Sahm et al. (2020) find that poorer individuals spend most of their checks to repay debt and that the richest individuals are those who save the largest share of the amount received. Misra et al. (2020) use transaction-level data from debit cards and find that about 40 percent of every dollar in stimulus is spent within the first four days from receipt and document geographical differences in spending. Li et al. (2020) also document geographical differences by using transaction-level data from debit cards owned by low-income households, but also find that the stimulus payments had a positive and sizable effect on spending for low-income households and that the positive effect from the stimulus payment was four times as high in absolute value as the negative effect that the lockdown had on spending for the same group. Positive effects on the poverty level were also found by Han et al. (2020.) All of these data findings are consistent with the models discussed above: the poor, the young, and those with children are likely to benefit from higher amounts of stimulus as they are more financially-constrained and would spend a higher amount of the transfer received for any check amount.

Difficulty to reach the most marginalized. Finally, while the most disadvantaged would benefit the most from these stimulus payments, Bitler et al. (2020) discuss how many individuals remained and still are in distress despite the unprecedented policy response due to delays in implementation, the modest payments outside of UI benefits, and statutory requirements that exclude individuals that would benefit the most from the payments themselves. In particular, Marr et al. (2020) estimate that 12 million non-tax-return filers who are eligible for the stimulus check did not automatically receive it and had to request it. Because of this extra hurdle, there was a nearly-20-percentage-point difference in the receipt rate of stimulus checks between those eligible individuals below and above the poverty rate, at the expense of the poorer individuals. The papers discussed suggest that an implementation which does not favor those who are the most in need is far from an optimal allocation of the stimulus checks and leads to payments being made to those who would consume less of the overall payment because of their better financial health, and therefore to a lower stimulus effect overall.

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