A Poorly Understood Disease? The Unequal Distribution of Excess Mortality Due to COVID-19 Across French Municipalities

BY Paul Brandily, Clément Brébion, Simon Briole & Laura Khoury

DISCUSSION PAPER

Institutt for samfunnsøkonomi
Department of Economics

SAM 15/2020
ISSN: 0804-6824
August 2020

A Poorly Understood Disease? The Unequal Distribution of Excess Mortality Due to COVID-19 Across French Municipalities*

Paul Brandily[1], Clément Brébion[2], Simon Briole[1,3], and Laura Khoury[4]

[1]Paris School of Economics, France

[2]Centre d'Études de l'Emploi et du Travail, France

[3]J-PAL Europe, France

[4]Norwegian School of Economics, Norway

July 2020

Abstract

While COVID-19 was responsible for more than 600,000 deaths worldwide as of July 24, 2020, very little is known about the socio-economic heterogeneity of its impact on mortality. In this paper, we combine several administrative data sources to estimate the relationship between mortality due to COVID-19 and poverty at a very local level (i.e. the municipality level) in France, one of the most severely hit countries in the world. We find strong evidence of an income gradient in the impact of the pandemic on mortality rates, which is twice as large in municipalities below the 25th percentile of the national income distribution than in municipalities above this threshold. We then show that both poor housing conditions and higher occupational exposure play a key role in this heterogeneity: taken together, these mechanisms account for up to 77% of the difference observed between rich and poor municipalities.

JEL classification: I14; I18; R00

Keywords: COVID-19 ; poverty; inequality; mortality; labor market; housing conditions

*We would like to thank Philippe Askénazy, Luc Behaghel, François Fontaine, Camille Hémet, Clément Malgouyres, Éric Maurin, Dominique Meurs as well as participants of the Labor Chair seminar at the Paris School of Economics for their valuable comments. We thank as well the *CASD* for providing us access to the data. We benefited from the Labor Chair at PSE and the LABEX OSE - ouvrir la Science Économique funding for data access. Declarations of interest: none. E-mail addresses: `paul.brandily@psemail.eu`; `clement.brebion@lecnam.net`; `simon.briole@psemail.eu`; `laura.khoury@nhh.no`

1 Introduction

While COVID-19 is directly responsible for at least 633,000 deaths around the globe, as of July 24,[1] we know very little on the heterogeneity of its impact on mortality across regions and individuals. In particular, while an emerging literature in the US shows that ethnic minorities exhibit higher levels of COVID-19 prevalence (Almagro and Orane-Hutchinson, 2020; Borjas, 2020; McLaren, 2020), the evidence on the heterogeneous effect of COVID-19 on mortality across income groups remains scarce.

In this paper, we explore this issue in the context of France, one of the most severely hit countries in the world. We combine several administrative data sources to estimate the relationship between mortality due to COVID-19 and poverty at the municipality level, a very detailed geographic scale (1,600 inhabitants and 15 sq.km per municipality, on average). Accurately estimating this relationship is one of the main challenges faced by the literature because of the limited availability and reliability of public data on mortality directly attributable to COVID-19.[2] We circumvent this issue by using exhaustive death records provided by the French National Statistical Institute (INSEE) on a daily basis and we focus on excess mortality, broadly defined as the deviation in mortality with respect to a reference (pre-COVID) period.

We also take advantage of a quasi experimental setting to identify the causal impact of COVID-19 on mortality at the municipality level. The evolution of mortality across time can be affected by confounding factors not directly related to COVID-19. One obvious factor relates to the very special life conditions implied by the lockdown, but health-related factors due to year-to-year variations in seasonal diseases may also have an impact on excess mortality.[3] To overcome this issue, we exploit the fact that the lockdown was uniformly implemented over the French territory on March 17 (up until May 11) while the spread of the epidemic was still very heterogeneous across regions. In particular, we can distinguish high-infection areas, where COVID-19 was already widely spread when the lockdown started, from low-infection areas, where the prevalence of COVID-19 was very low but where life conditions became completely identical to those of high-infection regions.[4] We build on this quasi-experimental setting by employing a triple-difference strategy that consists of comparing the evolution of mortality between rich and poor municipalities located

[1] Source: European Centre for Disease Prevention and Control.

[2] In particular, measures based on confirmed cases are likely to introduce a substantial downward bias due to limited (and unequally distributed) testing capacities (Borjas, 2020; Roser et al., 2020). For example, projections by Silverman et al. (2020) suggest that almost 80 percent cases of COVID-19 in the US were never officially diagnosed. Scarpetta et al. (2020) further show that France ranks among the worst OECD countries with respect to the number of tests per inhabitants.

[3] More specifically, differential effects of lockdown and/or seasonal diseases between rich and poor municipalities would bias our estimation of the heterogeneous impact of COVID-19 on mortality across municipalities.

[4] Government records indicate that, on March 17, the intensive care units occupancy rate was 8% in low-infection *départements* vs. 34.5% in high-infection *départements*.

in high-infection regions and in low-infection regions. Our analysis compares municipalities within urban areas to investigate the role of very local socio-economic determinants on the spread of the virus.

We find strong evidence of a positive relationship between municipalities' mortality due to COVID-19 and their poverty level. In high-infection regions, the pandemic caused a 50pp increase in mortality in most municipalities (relative to low-infection areas), but this increase actually reached 88pp for municipalities of the poorest quartile (i.e. municipalities where the median household income is below the 25^{th} percentile of the national income distribution). By contrast, the comparison of rich and poor municipalities in low-infection regions reveals no significant difference in the evolution of mortality.

Based on the same methodological approach, we then explore potential mechanisms explaining the causal relationship between mortality and poverty observed at the municipality level. While we acknowledge the key role that health factors may play at the individual level, we focus on two complementary mechanisms related to disease transmission channels at the municipality level.[5] Thanks to administrative and nearly exhaustive data, we are able to observe labor market and housing conditions of every municipalities' inhabitants. We first build two different measures of occupational exposure at the municipality level, based (i) on the frequency of social contacts under regular working conditions and (ii) on the share of essential workers that continued going to their workplace during the lockdown. Housing conditions are captured by the municipality-level share of overcrowded housing. Finally, to investigate the potential interaction between occupational exposure and housing conditions, we compute the share of multi-generational households that include at least one worker and an elderly person (over 65 y.o.).

A preliminary analysis confirms that all our indices measuring occupational exposure and poor housing conditions strongly relate to municipalities' poverty level. Further analysis shows that the share of overcrowded housing units unambiguously increases mortality due to the pandemic. We also find strong evidence that a greater occupational exposure in the municipality leads to an increased mortality, but this result is stronger when we use a measure of social contacts based on pre-lockdown working conditions rather than the share of essential workers, suggesting that the spread of the epidemic through the labour market was less pronounced during the lockdown. Finally, the share of multi-generational households significantly and positively relates to excess mortality, suggesting that the effects of poor housing conditions and occupational exposure on mortality may partially operate through working-age individuals

[5] An extensive literature provides evidence of substantial health inequalities across individuals of different socio-economic status (Adler and Rehkopf, 2008; Cutler et al., 2012). A recent work by Wiemers et al. (2020a) confirms a higher incidence of severe complications from COVID-19 among poor individuals. Further mechanisms may also include: greater levels of air pollution in poorer areas (Cole et al., 2020; Persico and Johnson, 2020) and lower levels of compliance to lockdown and to self-protection measures among low-income individuals Papageorge et al. (2020), among others. While population density is also an often debated mechanism, we do not treat it as a potential mechanism given its negative correlation with poverty in our data.

transmitting the virus to more vulnerable individuals in their household. A Oaxaca-blinder decomposition finally reveals that, taken together, these mechanisms account for up to 77% of the differential in mortality observed between rich and poor municipalities located in high-infection regions.

We make several contributions to the emerging literature on the socio-economic aspects of COVID-19's consequences and on the factors influencing the spread of COVID-19. A first strand of this literature highlights the unequal effects of the COVID crisis on individuals' labor market outcomes.[6] These papers tend to show that the crisis primarily affected the income and risk of job loss of vulnerable groups, especially ethnic minorities and low-paid workers.[7] Some recent works also provide evidence on the unequal distribution of COVID-19 infection rates and related mortality across ethnic groups (Bertocchi and Dimico, 2020; Borjas, 2020; McLaren, 2020; Sa, 2020). Another strand of the literature studies the potential channels of transmission of the epidemic. In particular, recent works focus on the role of occupational exposure (Almagro and Orane-Hutchinson, 2020; Lewandowski, 2020), economic activities' concentration (Ascani et al. (2020)), urban density (Carozzi (2020)), presence of care homes (Alacevich et al. (2020)), mass protests (Dave et al. (2020)) or elections (Bach et al. (2020)) in the spread of the epidemic.

Our main contribution is to provide clear evidence of a substantial income gradient in the impact of the pandemic on mortality, and to highlight the key role played by poor housing conditions and occupational exposure in explaining this income gradient in the impact of COVID-19 on mortality. More generally, we also show that both occupational exposure and poor housing conditions act as powerful transmission channels of the epidemic. As compared to previous papers, we are able to base our analysis on exhaustive data available at a very local level for a large population. To the best of our knowledge, our paper is also one of the first to study potential transmission channels based on excess mortality rather than infection rates or fatalities officially attributed to COVID-19. Finally, we develop a triple difference estimation strategy that allows us to isolate the effect of COVID-19 from that of lockdown on excess mortality.

The remainder of the paper is organized as follows: section 2 describes the mortality data and the construction of our outcome variable. In section 3, we present our empirical strategy before estimating the link between poverty and excess mortality due to COVID-19 in section 4. Given these results, in section 5 we explore potential mechanisms and in section 6 we present our conclusion.

[6]See e.g. Adams-Prassl et al. (2020); Alstadsæter et al. (2020); Borjas and Cassidy (2020); Dingel and Neiman (2020); Fairlie et al. (2020); Montenovo et al. (2020); Yasenov (2020)

[7]However, Forsythe et al. (2020) also show that the crisis had a strong short-term impact on job vacancies and UI claims in all industries and for most occupations in the US.

2 Measuring COVID-19 related mortality

In this paper, we gather various data sets using municipality-level identifiers. In France, municipalities are small administrative units of 1,600 inhabitants and 15.3 sq.km on average (as of 2014); there are about 35,000 of them in 2020. Our analysis compares municipalities *within* urban areas. Urban areas are groups of neighboring municipalities defined by the French National Statistical Institute (INSEE).[8] The majority of our sources are exhaustive administrative data sets made available by INSEE, we provide more details on all data in appendix B.

Mortality

To measure mortality due to COVID-19 at the municipality level, we rely on daily counts of deaths from INSEE. Data includes municipality and place (hospital or clinic, home, care home, etc.) of death as well as a set of individual-level characteristics such as sex, date of birth and municipality of residency.[9] Most of our analysis focuses on the month of April - when the peak of the epidemic in France occured (see Appendix D for a discussion and graphical evidence).

We use data on all-cause mortality data rather than COVID-19 cases or deaths, because the latter suffer from several limitations: first, testing was not randomly allocated over the territory during the period of observation, especially in the case of France that ranks among the worst OECD countries in number of tests per inhabitant (Scarpetta et al., 2020; Foucart and Horel, 2020; Borjas, 2020). Second, people who die from VIDOC-19 may not be accurately identified (e.g., if they die at home). According to Silverman et al. (2020) projections, almost 80% of cases of COVID-19 in the US were never diagnosed. Finally, to our knowledge, the only data available in France include people who died in hospital only, and at a less precise spatial level (*département*). Conducting the analysis at the municipal level is crucial as it allows for a closer examination of the socio-economic determinants of mortality due to COVID-19. Indeed, while the location of a new cluster within a country may be the result of many factors, the focus here is on the role of socio-economic factors in explaining the spread and severity of the epidemic at the local level.

[8]There are 706 urban areas in France with a median number of municipalities of 89 and a median population size of 221,105 inhabitants.

[9]In the emergency of the COVID-crisis, INSEE made the data set available at a high frequency rate: this has induced potential measurement errors although INSEE applies corrections at each iteration. We recognize this limitation and update our data as often as possible. Note that, in theory, municipalities have about one week to inform INSEE about new death. As the version of the data that we are currently using got downloaded on June 30, our measures should be accurate. For a discussion on the quality of the data, see the information provided by INSEE. We follow the guidelines detailed in this blog post.

Excess mortality

Our main outcome variable is excess mortality in April 2020. It is defined as the ratio between death rate in April 2020 and the average death rate in April 2018 and 2019.[10] Because we use the same population value (recorded in 2014) for the computation of all three death rates, it translates into the ratio of the number of deaths in April 2020 and the average of the number of deaths in April 2019 and 2018, as follows:

$$Death\_r_m = \frac{N_{m,2020}}{(N_{m,2018} + N_{m,2019})/2}$$

where $N_{m,y}$ is the number of deaths in municipality m in April of year y.

This definition of the excess mortality rate follows the guidelines defined by the Centre for Epidemiology of Medical Causes of Death of the French National Institute of Health and Medical Research (INSERM, CepiDc) available here. As it is a relative measure, it takes into account population size.[11]

The French National Institute of Health and Medical Research has used alternative measures in previous studies (SPF, 2019), such as the difference in the number of deaths:

$$Death\_r_m^{'} = N_{m,2020} - (N_{m,2018} + N_{m,2019})/2$$

We therefore provide a robustness check using this definition, and results hold (Table A5 of Appendix 6).

It has been shown that the likelihood of dying from COVID-19 is much higher among people over 65 years old (Wu and McGoogan, 2020).[12] However, to be as agnostic as possible, we use the total count of deaths, without specifically focusing on the elderly. We also report the coefficient of our main regression for different age groups in Appendix 6 (Figure A2).

Note that using all-cause excess mortality could create potential biases as it captures both the effect of COVID-19 and of the lockdown, and because it can be sensitive to random variations (Le Bras, 2020). We address these issues in two ways: (i) by measuring excess mortality over a month (so as to avoid day-to-day random variations in the number of deaths); (ii) by using an empirical strategy that isolates the effect of COVID-19 from that of the lockdown (see Section 3).

[10]We use the average of years 2018 and 2019 because taking several years makes our measure less sensitive to random events occurring in a given year. For data availability reasons, we cannot go further back in time, since death data before 2018 do not include, at the moment, information on the municipality of residency. However, INSEE advises against using too many years because demographic change makes the comparison of the number of deaths less relevant as we go further back in time.

[11]However, we also control for total population and population over 65 years old in our regressions.

[12]In its report of March 24, the National Public Health Agency (*Santé Publique France*) explains that the number of deaths of people under 65 y.o. without pre-existing conditions accounts for 2.4% of total deaths due to COVID-19 in France.

3 Empirical strategy

We take advantage of a quasi-experiment affecting the spread of the COVID-19 epidemic in France by employing a triple-difference strategy. Our main model (Equation 1) estimates the change in mortality rate at the municipality level over three dimensions: (i) time; (ii) the infection intensity of COVID-19 and (iii) income. The time dimension consists in comparing the number of deaths in April 2020 with the number of deaths in April 2018 and 2019. This difference does not explicitly appear in Equation 1 but is captured in the dependent variable $Death\_r_{m,ua,d}$, which is defined as the excess mortality rate in municipality m of urban area ua in *département* d (cf. section 2 above). The second difference in Equation 1 compares municipalities in low- and high-infection areas. For that purpose we define the indicator $Infect_d$ that takes the value one for municipalities in high-infection *départements* (indexed by d).[13] On May 7, the Ministry of Public Health published a map differentiating low- and high-infection areas, defined at the *département* level. Although this map dates from May and was made in order to guide the lockdown lifting across the country, it also appears to be a good proximate measure of the infection intensity before and during the lockdown. We provide more details in Appendix A and report the map in Figure A1. Finally, the third and last difference compares municipalities according to their median standard of living. We split municipalities in two groups and the variable $Poor_{m,ua,d}$ in Equation 1 indicates whether municipality m belongs to the poorest group. In section 4 below, we discuss the cut-off that we use to distribute municipalities across poorer and richer groups.

$$Death\_r_{m,ua,d} = \alpha + \delta.Infect_d + \lambda.Poor_{m,ua,d} + \rho.Infect_d.Poor_{m,ua,d} + \beta.X_{m,ua,d} + c_{ua} + \epsilon_{m,ua,d} \quad (1)$$

The main coefficient of interest is ρ which estimates the difference across high-infection and low-infection areas of the difference in excess mortality between rich and poor municipalities within given urban areas. $X_{m,ua,d}$ is a vector of controls that varies according to the specification. The most comprehensive one includes the total population and the population above 65 years old. Importantly, we introduce c_{ua}, an urban-area fixed-effect so that we only exploit differences between municipalities located in a contiguous urban environment. Municipalities are the smallest administrative units in France, and urban areas are greater statistical units made of multiple municipalities. Our results are thus valid when comparing units at a very fine spatial level.

[13] Relative to municipalities, *départements* are higher administrative units. There are 94 *départements* in mainland France, excluding Corsica.

This triple difference design takes advantage of a quasi-experiment: the uniform implementation of the lockdown in France (between March 17 and May 11) froze the epidemic at very different stages of development over the territory, while imposing identical restrictions for all areas. This design allows us to disentangle the impact of the epidemic from that of the lockdown. This is crucial as the effect of the lockdown on mortality is unclear and could be non-orthogonal to households' income.[14] However, the triple-difference design does not control for the risk that, coincidentally, the differences in COVID-19 infection intensity across areas at a given point in time could be non-orthogonal to areas' income level. To take this into account, we include urban-area fixed-effects in our model. Finally, we cluster standard errors at the *département* level, the most aggregated level of treatment status in our design. Note that clustering at the level of urban areas does not change the nature of our results.

This model identifies the causal effect of poverty on COVID-19 related excess mortality under the sole hypothesis that, absent COVID-19, the average difference in the evolution of mortality in April (2020 v.s. 2019 and 2018) between rich and poor municipalities of the same urban area would have been the same in high and low-infection *départements*.

4 Excess mortality due to COVID-19 and poverty

In this section, we show that, within urban areas, excess mortality due to COVID-19 was higher in poorer municipalities. We first uncover a non-linear relationship between within-urban-area income and excess mortality, showing that the poorest municipalities suffered more of COVID-19. We then turn to the estimation of Equation 1 to argue that this relationship is causal.

4.1 A non-linear relation between income and mortality due to COVID-19

In this subsection, we show that the relation between municipalities' income and excess mortality is not linear but driven by the poorest municipalities. These results are of importance *per se* but also because they inform our identification strategy and the way we define poor and rich municipalities.

To show that most of the excess mortality is driven by the poorest municipalities of French urban areas, we estimate Equation 2. Using tax data (the 2014 *Filosofi* database, see Appendix B for more details), we rank municipalities according to the median standard of living of their households, from the poorest quartile ($Q1$) to the richest quartile ($Q4$). We then regress our main dependent variable ($Death\_r_{m,ua,d}$, the municipality excess death ratio) on a set of dummies indicating each of the four quartiles (omitting

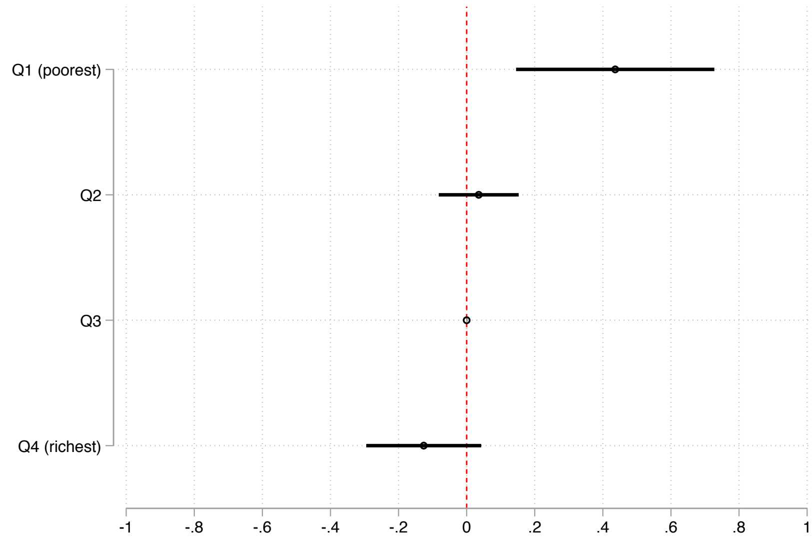
[14] On the impact of the lockdown on mortality rates see for instance Brodeur et al. (2020) - who have shown that deaths related to traffic accidents have dropped.

$Q3$ as the reference category) as well as a vector $X_{m,ua}$ of municipality characteristics and urban-area fixed-effects (γ_{ua}), separately for low- and high-infection *départements*. Standard errors are clustered at the *département* level.

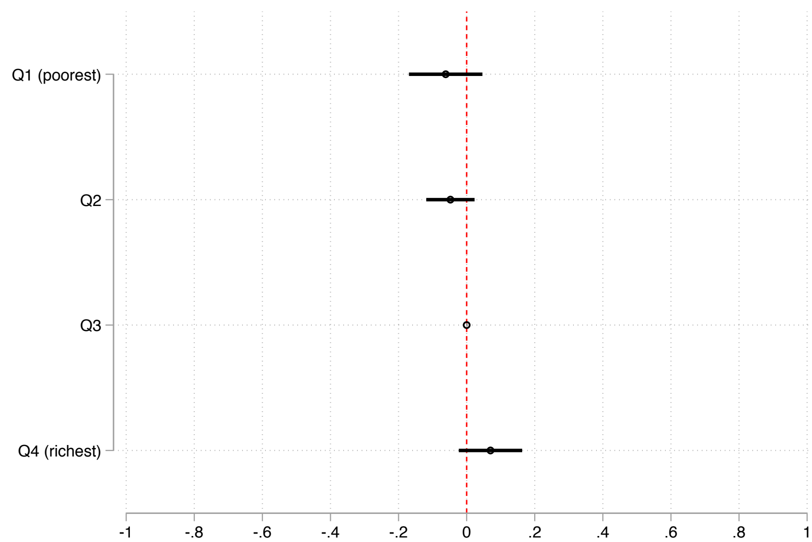
$$Death\_r_{m,ua,d} = c + \beta_1.Q1_{m,ua} + \beta_2.Q2_{m,ua} + \beta_4.Q4_{m,ua} + X_{m,ua}.\Lambda + \gamma_{ua} + \nu_{m,ua} \quad (2)$$

Figure 1 plots the estimated coefficients β_1, β_2 and β_4 (and their 95% confidence interval) for urban areas in high-infection *départements* (1(a)) and in low-infection *départements* (1(b)). Figure 1(a) shows a marked difference between the excess mortality in the bottom quartile and in the other groups. On average, within high-infection urban areas, the rise in the number of deaths that occurred in bottom-quartile municipalities (between April 2020 and both April 2019 and 2018) is 40 percentage points larger than in municipalities of the 3^{rd} quartile. Excess mortality in the other quartiles follows a weak trend in income but no difference across these groups is significant at the 5% level. Strikingly also, such pattern is absent in low-infection urban areas. The poorest municipalities of these urban areas do not show excess mortality levels that are significantly different from richer municipalities. We take these first results as evidence that COVID-19 increased excess mortality in the poorest municipalities within high-infection urban areas. This result is robust to alternative definition of income.[15]

[15] For instance, we also partitioned the distribution of income by deciles. In high-infection areas, the bottom three deciles show similar excess mortality levels that are significantly different from municipalities in the 5^{th} decile. Deciles four as well as deciles six to ten are not significantly different in terms of mortality from the 5^{th} decile. Hence our choice to work at the quartile level in the end.



(a) High-infection zone



(b) Low-infection zone

Figure 1: Excess mortality according to municipalities' income

Note: This Figure shows the 95% confidence intervals of the coefficients estimated in Equation 2 - that is the regression of excess mortality on quartiles of the distribution of municipalities' income, on controls and on urban areas fixed effects. Regressions are separately led in high-infection *départements* (Figure 1(a)) and low-infection ones (Figure 1(b)).

4.2 The causal impact of poverty on excess mortality due to COVID-19

In this subsection, we argue that the relation between municipality income and excess mortality in April 2020 shown in Figure 1 is causal and due to COVID-19. Our argument is based on the main hypothesis that, absent COVID-19, the difference in the average evolution of mortality in April (2020 vs. 2019 and 2018) between rich and poor municipalities of each urban area would have been the same across (actually) high-infection and low-infection *départements*. To support this hypothesis, we first present graphical evidence of the change in mortality across municipalities' income between high-infection and low-infection areas over time. We then estimate the corresponding triple-difference model.

Figure 2 displays the binned scatter plot of the average number of deaths per year, controlling for total population, population above 65 years old and urban-area fixed effects, separately for municipalities from the bottom quartile (red line) and the other three (blue line). The left panel is based on low-infection *départements* only. On that sample, there is a small rise in deaths in 2020 compared to previous years but the evolution is comparable across poor and rich municipalities, although slightly higher for the lowest quartile of income. In high-infection areas however (right panel), the pattern is dramatically different: in 2020, mortality sharply increased and much more so in the lowest quartile municipalities than in richer municipalities. Importantly, changes in mortality over the pre-COVID period (2018-2019) were very similar in poor and rich municipalities (i.e. the trends were parallel) and in high- and low-infection *départements*. This last piece of evidence supports the hypothesis that, absent COVID-19, the evolution of within urban-areas differences in mortality between rich and poor municipalities would have been the same in high- and low-infection *départements*; while it is not possible to test such hypothesis, we take Figure 2 as a strong argument in its favor.

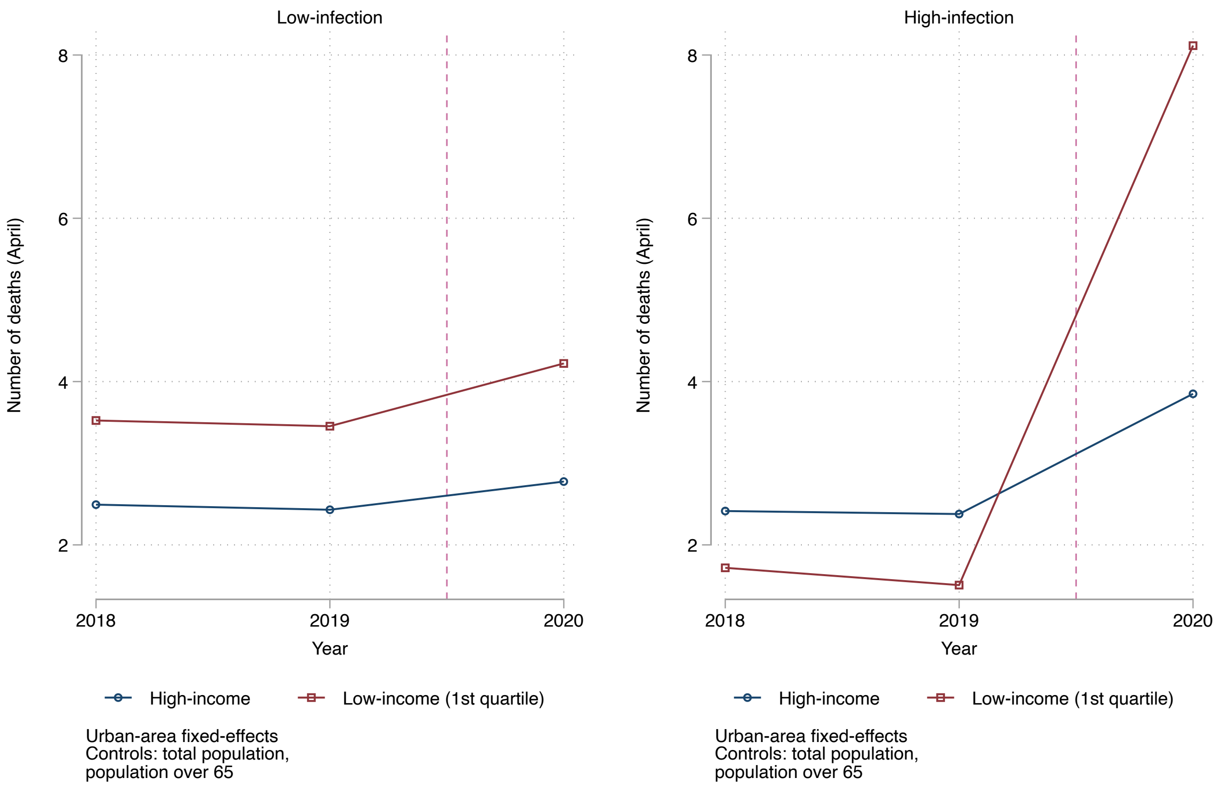


Figure 2: Municipalities' mortality between 2018 and 2020 according to municipalities' poverty level

Note: This Figure shows the evolution of municipalities' average number of deaths during the month of April between 2018 and 2020, separately for municipalities whose median income is lower than the first quartile of French municipalities' median income (red) and municipalities above that threshold (blue). The left (right) hand graph corresponds to municipalities located in low (high) infection *départements*. All estimations control for urban area fixed effects, total population and share of population above 65 years old.

Estimands of Equation 1 displayed in Table 1 provide further evidence that the relation between poverty and excess mortality due to COVID-19 is positive and that it is driven by the poorest municipalities. In line with what precedes, panel A of columns (1) and (2) shows results where the poverty cut-off is the first quartile of municipalities' median income. In rich municipalities located in low-infection *départements*, the average number of deaths in April 2020 is 110% of the average number of fatalities in 2019 and 2018. This limited rise is potentially due to COVID-19 but we do not disentangle its causes and consider it as a baseline scenario for 2020 (that is the most conservative approach). The contrast with high-infection areas is striking: in these areas, mortality in rich municipalities in April 2020 is 160% of that of April 2019 and 2018 (i.e. a 0.50 increase in the average excess mortality ratio of 1.1 in non-poor, low-infection municipalities). Most importantly for us, while the impact of income on excess mortality is not significantly different from zero in low-infection *départements*, it is strongly and significantly positive in high-infection *départements*. In these *départements*, COVID-19 has caused an excess mortality that is 38 percentage points larger on average in municipalities of the bottom quartile of the income distribution than in richer municipalities. That is to say, poorest municipalities saw their mortality double. These results are qualitatively unchanged when we compare municipalities above or below the median of the national distribution of median income (see columns (3) and (4)). We also discuss the evolution of 2020 mortality over time (on a pair-of-week approach) in Appendix D.

Table 1: Excess mortality due to COVID-19 according to municipalities' poverty level

	(1)	(2)	(3)	(4)
Infected Region	0.56765***	0.50295***	0.55603***	0.49125***
	(0.15339)	(0.14053)	(0.15971)	(0.14508)
Very poor (Quart1)	-0.03873	-0.04777		
	(0.04827)	(0.04885)		
Infected*Quart1	0.50212***	0.42904***		
	(0.13412)	(0.11738)		
Poor			-0.05926*	-0.05818*
			(0.03207)	(0.03177)
Infected*Poor			0.27501***	0.21982***
			(0.07986)	(0.06735)
Control outcome mean	1.105	1.105	1.130	1.130
Urban areas FE	✓	✓	✓	✓
Controls	.	✓	.	✓

Note: This table shows the result of regressing municipalities' excess mortality in April 2020 on a dummy indicating that the municipality is located in a high-infection *département*, a dummy indicating that the municipality's median income is under the poverty cut-off and the interaction of these dummies, using the ratio definition of excess mortality (i.e., number of deaths in April 2020 as compared to April 2018 and 2019). The poverty cut-off in columns (1) and (2) corresponds to the first quartile of municipalities' median income, while it corresponds to the median of municipalities' median income in columns (3) and (4). All regressions include urban areas fixed-effects. Regressions in columns (2) and (4) further control for total population and for the age structure in the municipality. The control outcome mean line reports the mean of the excess mortality rate in low-infection-non-poor municipalities. Standard errors in parentheses are clustered at the *département* level. * p<0.10, ** p<0.05, *** p<0.01.

5 Potential mechanisms

In this section, we explore the role of two potential mechanisms that could explain the relationship between poverty and COVID-19 related mortality: labor-market exposure (section 5.1) and housing conditions (section 5.2).

We chose these two channels informed by current literature about how COVID-19 is transmitted. We of course acknowledge that these are only two potential mechanisms among many, that poverty is multidimensional and that we notably ignore the role of comorbidities known to be related with poverty and that most likely played a role in the observed phenomenon (Wiemers et al., 2020b; Raifman and Raifman, 2020). In other words, we do not aim to identify all the potential channels but intend to quantify the respective role of labor-market and housing conditions in explaining the difference in mortality between poorer and richer municipalities.

5.1 Labor Market and Exposure to COVID-19

5.1.1 Measures

We explore the idea that low-paid occupations are also more exposed to COVID-19 transmission. Our hypothesis is that some occupations may be at higher risk, because of the nature of work in the pre-lockdown period or because they continued to operate during the lockdown. Specifically, we build a first measure of exposed occupations using a survey called "DEFIS" that gives a proximate measure of "direct contact with the public" for each 3-digit level occupation code. This survey is informative on the usual business conditions and is most relevant to analyse the impact of pre-lockdown exposure. We next exploit the list of essential workers from the Paris Region Health Observatory. This list details occupations and sectors of workers that kept on going to their workplace during lockdown. We provide more details about the construction of these measures in Appendix A and reference the sources in Appendix B. Appendix 2 shows descriptive statistics.

To quantify the municipality level labor-market exposure to COVID-19, we map our two occupational measures to exhaustive social security records called DADS. The DADS is an exhaustive administrative data set that firms are compelled by law to fill-in yearly (cf. Appendix B). In particular, for virtually any worker in France, we observe: the occupation and sector of employment (both at the highest level of precision), municipality of work and municipality of residency. This allows us to compute (i) the worker-weighted average frequency of contact (hereafter "index of frequent contact") and (ii) the share of essential workers in every French municipality.

Table A2 shows the strength of the link between poverty and our labor-market measures, once included our baseline covariates and urban-area fixed-effects. In both cases, municipalities of the poorest quartile have more occupations in contact with the public (first column of Panel A) and more essential workers (second column of Panel A).[16]

5.1.2 Results

We now estimate the triple difference model exposed in Equation 1 but substituting labor-market-related measures in place of the poverty indicator. Table 2 reports the main coefficient of interest (i.e. the ρ of Equation 1).

Both labor-market indices have a significant effect on excess mortality. The first column of Panel A of Table 2 indicates that when the share of frequent-contact jobs increases by 1pp in highly infected *départments*, excess mortality in April increases by about 2.56 percentage points. Put differently, increasing the share of frequent-contact workers by one standard-deviation (0.046) increases excess mortality by 12pp. Although the share of essential workers has a significant effect on excess mortality, our findings suggest that pre-lockdown occupational exposure is the most important determinant. Indeed, as displayed in Appendix 4, when both labor-market indices are included in the regression, the coefficient of the share of essential workers loses its significance. Further, the correlation between the two variables is sizeable (0.46). Graphical evidence also supports this interpretation: Figure A5 (Appendix D) shows that the weekly effect of the share of essential workers and of the index of frequent contact have the same pattern. Would the former play a role independently of the latter, its effect should be a bit delayed. Taken together, these results suggest that a larger share of essential workers rises mortality mostly through its induced effect on pre-lockdown exposure.

5.2 Housing Conditions

5.2.1 Measures

Regarding housing conditions, we use Census data to measure the share of overcrowded housing units in the municipality (cf. Appendices A and Appendix 2 for more details.). By multiplying the probability

[16] In Panel A of Table A2, the outcome means indicates that 9% of municipalities in our sample belong to the first quartile. That share is unsurprisingly lower than 25% since the poverty variable is defined by weighting municipalities by their population size. The first column indicates that, within an urban area, increasing the share of frequent-contact workers by 1pp rises the probability to fall in the poorest quartile by 0.48pp. Or, a one standard deviation increase in the share of frequent-contact workers is associated with a 2.3pp increase in excess mortality. The second column shows that a 1pp (respectively one standard deviation) increase in the share of essential workers increases the probability to fall in the poorest quartile by 0.91pp (respectively 9pp).

of social contacts (either within the household or by increasing the need of going out), overcrowding is an obvious candidate for COVID-19 transmission. In Table A2, column 4 of Panel A indicates that within urban areas and given population size and age-structure, poorest municipalities have more overcrowded housing units.[17]

5.2.2 Results

We estimate the triple difference model exposed in Equation 1 but substituting the municipality-level share of over-crowded housing in place of the poverty indicator.

As shown by Table 2, increasing the share of overcrowded housing by 1pp increases excess mortality by 5.6pp. In other words, and to get a sense of the magnitude of this effect, increasing the share of over-crowded housing units by one standard-deviation (.025) increases the excess mortality by 14pp. This is a very important effect, of comparable size with the estimates related to contacts on the labor market.

5.3 Interacting Labor-Market and Housing Conditions

5.3.1 Measures

We complement our study of labor-market and housing conditions by taking one measure at the interaction of these two dimensions. Using exhaustive files from the Census, we compute the share of municipalities' households that gather at least one member aged 65 or more and one member from a younger generation who is currently employed (see appendix A for more details on this measure). This measure requires occupation information from the Census, which are only measured in municipalities with at least 2,000 inhabitants and we thus report the associated results in Panel B of Table A2. Here again, poorest municipalities are much more likely to have such type of multigenerational households.[18]

5.3.2 Results

In Panel B of Table 2, we observe that households including both elderly and employed individuals seem to foster the transmission of COVID-19 and its associated mortality. We find that increasing the share of such households by 1pp would increase excess mortality by 12pp, which happens to be equivalent to the effect of a one standard-deviation increase. Since this last measure is only observed on a sample of municipalities with more than 2,000 inhabitants, we also reproduce our results of Panel A (for our main

[17] A 1pp (respectively one standard-deviation) increase in the municipality's share of over-crowded housing is associated with a 2.4pp (respectively 6pp) increase in the probability to fall in the bottom 25% of the income distribution.

[18] The coefficient indicates that a 1pp (that happens to be the size of one standard-deviation) increase in the share of multigenerational households increases the probability to be in the poorest quartile by 2.03pp.

three variables) on that sample. All the point estimates are of the same magnitude, although standard errors are larger due to the smaller sample size.

Table 2: Effect of Covid-19 on excess mortality - All mechanisms

	Occupational exposure mechanism		Housing mechanism
	Index of frequent contact	Share of essential workers	Share of over-crowded housing
Panel A: All urban areas			
Main coefficient	2.56144***	0.97819*	5.65638***
	(0.81134)	(0.50663)	(1.02754)
Control outcome mean	1.036	1.036	1.043
Observations	13471	13471	12918
Panel B: Urban areas with more than 2000 inhabitant cities			
Main coefficient	3.95791	0.47059	5.84591***
	(2.75105)	(1.24708)	(1.93072)
Outcome mean	1.314	1.314	1.319
Observations	3671	3671	3653
	Interaction of both mechanisms		
	Share of multi-generational hh with at least one worker		
Panel B: Urban areas with more than 2000 inhabitant cities			
Main coefficient	12.16877**		
	(5.82533)		
Control outcome mean	1.314		
Observations	3671		
Urban areas FE	✓	✓	✓
Controls	✓	✓	✓

** p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses are clustered at the département level.* This table shows the result of regressing municipalities' excess mortality in April 2020 on a dummy indicating that the municipality is located in a high-infection *département*, a variable measuring either housing conditions or occupational exposure and the interaction of these variables, using the ratio definition of excess mortality (i.e. number of deaths in April 2020 as compared to April 2018 and 2019). Each column reports the result of a separate regression examining one mechanism. The main coefficient corresponds to the interaction term between the variable of interest and the high-infection *département* dummy. All regressions include urban areas fixed-effects and control for total population and for the age structure in the municipality. The control outcome mean line reports the mean of the excess mortality rate in low-infection municipalities.

5.4 Disentangling the role of each mechanism

To understand which mechanism prevails, we perform a horse race between variables related to occupational exposure and housing conditions. Table 3 reports the results. When comparing column (1) with columns (2) to (4), we observe that the inclusion of the share of overcrowded housing makes the coefficient of poverty shrink.[19] Other variables have only a minor effect on the poverty coefficient. The initial coefficient of poverty diminishes by 45% when all covariates are included, although housing conditions and the index of occupational contact still play a significant role in explaining excess mortality. Confirming a previous observation, the effect of being an essential worker drops when the contact variable is included. All in all, it suggests that both housing conditions and the frequency of social contacts through occupations are important determinants of the relatively higher excess mortality due to COVID-19 in poor municipalities, but that housing conditions appear to be the main determinant.

This analysis is confirmed by a Oaxaca-Blinder decomposition (Table A4 of Appendix 5) that quantifies the share of the gap in excess mortality between poor and rich municipalities within urban areas in high-infection *départements* that is explained by the included covariates (Oaxaca, 1973; Blinder, 1973). While 77% of the 39 percentage points difference in excess mortality rate between rich and poor municipalities within urban area is explained by the mechanism variables (cf. column 1), the sole share of overcrowded housing contributes 84% of these 77%, that is 65% of the total difference. This decomposition is based on certain assumptions but, if anything, confirms that housing conditions are the main determinant of the within-urban-area gap in excess mortality between rich and poor municipalities.

Table 3: Effect of each covariate on excess mortality due to COVID-19

	Excess Mortality Rate, april 2020				
Infected Region=1 × Very poor (Quart1)	0.17657***	0.16974***	0.15185***	0.10817**	0.09762**
	(0.04831)	(0.04423)	(0.04630)	(0.04338)	(0.04120)
Infected Region=1 × Index of frequent contact		0.12227***			0.08334**
		(0.04005)			(0.04080)
Infected Region=1 × Share of essential workers			0.09659*		0.02827
			(0.05695)		(0.05992)
Infected Region=1 × Share of over occupied housing units				0.12320***	0.11403***
				(0.02768)	(0.02823)
Urban areas FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Control outcome mean	1.038	1.038	1.038	1.043	1.043
Adjuster R^2	0.0441	0.0489	0.0499	0.0527	0.0581
Observations	13219	13219	13219	12912	12912

** p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses.* This table shows the result of regressing municipalities' excess mortality in April 2020 on a dummy indicating that the municipality is located in a high-infection *département*, a variable measuring either poverty, housing conditions or occupational exposure and the interaction of these variables, using the ratio definition of excess mortality (i.e. number of deaths in April 2020 as compared to April 2018 and 2019). The first columns only examines the poverty channel. Columns (2) to (4) respectively include one additional variable capturing either the occupation or housing mechanism. The last column includes both the poverty dummy and all the mechanism variables. All regressions include urban areas fixed-effects and control for total population and for the age structure in the municipality. Each covariate has been normalized. The control outcome mean line reports the mean of the excess mortality rate in low-infection municipalities.

[19] All covariates have been normalized to ease comparison.

6 Conclusion

In this paper, we provide clear evidence that COVID-19 disproportionately affects the poor. The impact of the epidemic on excess mortality is twice as large in the poorest French municipalities, though it also caused a significant rise in mortality in other municipalities where the virus actively circulated. We further show that both a higher share of workers frequently in contact with the public and a higher share of overcrowded housing explain a substantial part of the link between poverty and COVID-19 related mortality. While such results highlight the amplifying effect of the epidemic crisis on socio-economic inequalities, they also suggest that targeting resources at poor municipalities would be an appropriate response to the crisis, especially in order to protect workers as much as possible in the short run and to improve housing conditions in the medium run.

References

Abi Adams-Prassl, Teodora Boneva, Marta Golin, and Christopher Rauh. Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *CEPR Discussion Paper No. DP14665*, 2020.

Nancy E Adler and David H Rehkopf. Us disparities in health: descriptions, causes, and mechanisms. *Annu. Rev. Public Health*, 29:235–252, 2008.

Caterina Alacevich, Nicolò Cavalli, Osea Giuntella, Raffaele Lagravinese, Francesco Moscone, Catia Nicodemo, et al. Exploring the relationship between care homes and excess deaths in the covid-19 pandemic: Evidence from italy. Technical report, Institute of Labor Economics (IZA), 2020.

Milena Almagro and Angelo Orane-Hutchinson. The determinants of the differential exposure to covid-19 in new york city and their evolution over time. *Covid Economics: Vetted and Real-Time Papers*, (13), 2020.

Annette Alstadsæter, Bernt Bratsberg, Gaute Eielsen, Wojciech Kopczuk, Simen Markussen, Oddbjorn Raaum, and Knut Røed. The first weeks of the coronavirus crisis: Who got hit, when and why? evidence from norway. Technical report, National Bureau of Economic Research, 2020.

Andrea Ascani, Alessandra Faggian, Sandro Montresor, et al. The geography of covid-19 and the structure of local economies: the case of italy. Technical report, 2020.

Laurent Bach, Arthur Guillouzouic, and Clément Malgouyres. Does holding elections during a covid-19 pandemic put the lives of politicians at risk? *PSE working paper N 2020 – 45*, 2020.

Graziella Bertocchi and Arcangelo Dimico. Covid-19, race, and redlining. Technical report, Institute of Labor Economics (IZA), 2020.

Alan S. Blinder. Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, 8(4):436–455, 1973. ISSN 0022-166X. doi: 10.2307/144855. URL https://www.jstor.org/stable/144855. Publisher: [University of Wisconsin Press, Board of Regents of the University of Wisconsin System].

George J. Borjas. Demographic Determinants of Testing Incidence and COVID-19 Infections in New York City Neighborhoods. SSRN Scholarly Paper ID 3572329, Social Science Research Network, Rochester, NY, April 2020. URL https://papers.ssrn.com/abstract=3572329.

George J Borjas and Hugh Cassidy. The adverse effect of the covid-19 labor market shock on immigrant employment. Technical report, National Bureau of Economic Research, 2020.

Abel Brodeur, Nikolai Cook, and Taylor Wright. On the Effects of COVID-19 Safer-At-Home Policies on Social Distancing, Car Crashes and Pollution. Technical Report 13255, Institute of Labor Economics (IZA), May 2020. URL https://ideas.repec.org/p/iza/izadps/dp13255.html. Publication Title: IZA Discussion Papers.

Felipe Carozzi. Urban density and covid-19. Technical report, Institute of Labor Economics (IZA), 2020.

Matthew Cole, Ceren Ozgen, and Eric Strobl. Air pollution exposure and covid-19. Technical report, Institute of Labor Economics (IZA), 2020.

David M Cutler, Adriana Lleras-Muney, and Tom Vogl. Socioeconomic status and health: Dimensions and mechanisms. In *The Oxford Handbook of Health Economics*. 2012.

Dhaval M Dave, Andrew I Friedson, Kyutaro Matsuzawa, Joseph J Sabia, and Samuel Safford. Black lives matter protests, social distancing, and covid-19. Technical report, National Bureau of Economic Research, 2020.

Jonathan I. Dingel and Brent Neiman. How many jobs can be done at home? *Journal of Public Economics*, 189:104235, 2020. ISSN 0047-2727.

Robert W Fairlie, Kenneth Couch, and Huanan Xu. The impacts of covid-19 on minority unemployment: First evidence from april 2020 cps microdata. Technical report, National Bureau of Economic Research, 2020.

Eliza Forsythe, Lisa B. Kahn, Fabian Lange, and David Wiczer. Labor demand in the time of covid-19: Evidence from vacancy postings and ui claims. *Journal of Public Economics*, page 104238, 2020. ISSN 0047-2727.

Stéphane Foucart and Stéphane Horel. Dépistage du coronavirus : les raisons du fiasco français sur les tests. *Le Monde.fr*, April 2020. URL https://www.lemonde.fr/planete/article/2020/04/24/nous-attendons-d-etre-contactes-par-l-ars-mais-il-ne-se-passe-rien-le-fiasco-des-tests-en-fran 6037647_3244.html.

Hervé Le Bras. L'épidémie et son terrain social, June 2020. URL https://jean-jaures.org/nos-productions/l-epidemie-et-son-terrain-social. Library Catalog: jean-jaures.org.

Piotr Lewandowski. Occupational exposure to contagion and the spread of covid-19 in europe. Technical report, Institute of Labor Economics (IZA), 2020.

Catherine Mangeney, Nathalie Bouscaren, Maylis Telle-Lamberton, Adrien Saunal, and Valérie Féron. La surmortalité durant l'epidémie de covid-19 dans les départements franciliens. Technical report, Paris Region Health Observatory, 2020. URL https://www.ors-idf.org/nos-travaux/publications/la-surmortalite-durant-lepidemie-de-covid-19-dans-les-departements-franciliens.html.

John McLaren. Racial disparity in covid-19 deaths: Seeking economic roots with census data. Technical report, National Bureau of Economic Research, 2020.

Laura Montenovo, Xuan Jiang, Felipe Lozano Rojas, Ian M Schmutte, Kosali I Simon, Bruce A Weinberg, and Coady Wing. Determinants of disparities in covid-19 job losses. Technical report, National Bureau of Economic Research, 2020.

Ronald Oaxaca. Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, 14(3):693–709, 1973. ISSN 0020-6598. doi: 10.2307/2525981. URL https://www.jstor.org/stable/2525981. Publisher: [Economics Department of the University of Pennsylvania, Wiley, Institute of Social and Economic Research, Osaka University].

Nicholas W Papageorge, Matthew V Zahn, Michèle Belot, Eline van den Broek-Altenburg, Syngjoo Choi, Julian C Jamison, Egon Tripodi, et al. Socio-demographic factors associated with self-protecting behavior during the covid-19 pandemic. Technical report, Institute of Labor Economics (IZA), 2020.

Sylvain Papon and Isabelle Robert-Bobée. Une hausse des décès deux fois plus forte pour les personnes nées à l'étranger que pour celles nées en france en mars-avril 2020. Technical report, French National Statistical Institute (INSEE), 2020. URL https://www.insee.fr/fr/statistiques/4627049.

Claudia Persico and Kathryn R Johnson. The effects of increased pollution on covid-19 cases and deaths. *Available at SSRN 3633446*, 2020.

Matthew A. Raifman and Julia R. Raifman. Disparities in the Population at Risk of Severe Illness From COVID-19 by Race/Ethnicity and Income. *American Journal of Preventive Medicine*, 59(1):137–139, July 2020. ISSN 0749-3797. doi: 10.1016/j.amepre.2020.04.003. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7183932/.

Max Roser, Hannah Ritchie, Esteban Ortiz-Ospina, and Joe Hasell. Coronavirus disease (covid-19)–statistics and research. *Our World in data*, 2020.

Filipa Sa. Socioeconomic determinants of covid-19 infections and mortality: Evidence from england and wales. Technical report, Institute of Labor Economics (IZA), 2020.

Stefano Scarpetta, Mark Pearson, Francesca Colombo, and Frederico Guanais. Testing for covid-19: A way to lift confinement restrictions. *OECD Policy Responses to Coronavirus (COVID-19)*, May 2020. URL https://www.oecd.org/coronavirus/policy-responses/testing-for-covid-19-a-way-to-lift-confinement-restrictions-89756248/#boxsection-d1e31.

Justin D Silverman, Nathaniel Hupert, and Alex D Washburne. Using influenza surveillance networks to estimate state-specific prevalence of sars-cov-2 in the united states. *Science translational medicine*, 2020.

SPF. Évaluation de la surmortalité pendant les canicules des étés 2006 et 2015 en france métropolitaine, April 2019. URL https://www.santepubliquefrance.fr/content/download/209360/2415511.

Emily E Wiemers, Scott Abrahams, Marwa AlFakhri, V Joseph Hotz, Robert F Schoeni, and Judith A Seltzer. Disparities in vulnerability to severe complications from covid-19 in the united states. Technical report, National Bureau of Economic Research, 2020a.

Emily E. Wiemers, Scott Abrahams, Marwa AlFakhri, V. Joseph Hotz, Robert F. Schoeni, and Judith A. Seltzer. Disparities in Vulnerability to Severe Complications from COVID-19 in the United States. *medRxiv*, page 2020.05.28.20115899, June 2020b. doi: 10.1101/2020.05.28.20115899. URL https://www.medrxiv.org/content/10.1101/2020.05.28.20115899v3. Publisher: Cold Spring Harbor Laboratory Press.

Zunyou Wu and Jennifer M McGoogan. Characteristics of and important lessons from the coronavirus disease 2019 (covid-19) outbreak in china: summary of a report of 72 314 cases from the chinese center for disease control and prevention. *Jama*, 323(13):1239–1242, 2020.

Vasil I Yasenov. Who can work from home? Technical report, Institute of Labor Economics (IZA), 2020.

A Appendix 1 - Measurement

1 High- and low-infection *départements*

When deciding the gradual lifting of the lockdown, the Ministry of Public Health provided a map differentiating red (high-infection) and green (low-infection) *départements* on May 7. This map distinguishes high- and low-infection areas on the basis of: (i) the share of ER visits for a COVID-19 suspicion; (ii) the occupancy rate of intensive care beds relative to the initial one; (iii) the testing rate relative to the needs. High-infection *départements* correspond to 41% of the population and to roughly 30% of mainland France *départements*, all in the North-Eastern quarter of the country.

Although published in May, we use this distinction as a proximate measure of COVID-19 spread intensity before and during lockdown. We can verify that, for instance, government records indicate that, on March 17, the intensive care units occupancy rate was 8% in low-infection vs. 34.5% in high-infection *départements*.

2 Labor Market Conditions

One of the main novelties of this paper is to use administrative data to test whether labor market conditions explain the differential in excess mortality between poor and rich municipalities. We focus on two main characteristics of jobs that we expect to be key vectors for spreading the disease: (i) whether the worker kept on going to her workplace during the lockdown; (ii) whether the job involves frequent contacts with the public in usual business conditions (i.e. as measured before the lockdown).

As for the first dimension, for each municipality, we compute the share of essential workers[20] based on individual employment data from the DADS and on a list of essential occupations built by the Paris Region Health Observatory (Mangeney et al., 2020).[21] Note that, although this list was built by an administrative organisation, it remains arbitrary by nature. However, to our knowledge, there is no better way at the moment to characterise workers that kept on going to their workplace during the lockdown.[22]

As for the second dimension, our proxy is based on the question "In your job, are you in direct contact with the public" that is available in a survey called DEFIS (see Appendix B). For each occupation code

[20] Workers are localised according to their municipality of residency and regardless of their municipality of work.

[21] Essential workers include: health workers, auxiliary nurses, pharmacists, ambulance drivers, post office clerks, the police, public transport and funeral services, firefighters, persons working in the sale of food products, delivery workers, tobacconists and cleaning staff. On average, they include about 19.5% of workers in each municipality. The French National Statistical Institute also used this list in one of their paper (Papon and Robert-Bobée, 2020).

[22] We tried an alternative approach based on sectors that remained active during the lockdown. Our results got very noisy as we could not systematically identify firms that remained open and workers that kept on going to their workplace at a disaggregated level.

(at the 3-digit level), we compute the share of workers answering “Often” (v.s. “Sometimes” or “Never”). Using the DADS, we then compute the average of this index at the municipality level based on the occupation distribution of workers living in each municipality.

3 Housing Conditions

Our last dimension of interest is the relation between housing conditions and excess mortality due to COVID-19. We use the average share of housing units that are overcrowded provided by INSEE at the municipality level. Overcrowded accommodations are those that have less than “one living room, one room for each couple, one room for each other adult aged 19 or older, one room for two children if they are of the same sex or are under 7 years of age, and one room per child otherwise”.

4 Interaction between Labor Market and Housing Conditions

To investigate the interactions between both mechanisms, we finally build an index at the municipality level, based on the partial census data files available for municipalities with more than 2,000 inhabitants. We compute the share of households with both an elderly person (over 65 y.o.) and a worker that is younger by at least 18 years (“multi-generational households” hereafter). This variable is meant to capture the fact that having different generations living in the same apartment increases the likelihood to get infected, and to potentially die for the elderly. This likelihood increases further if at least one of the younger members of the household works, as it potentially multiplies her social interactions.

B Appendix 2 - Data Sources

by alphabetical order

DADS (for "Déclarations Annuelles des Données Sociales") is a matched employer-employee exhaustive data set that covers all employees in private and public sectors (outside of agriculture) in the year 2016. The DADS is an administrative data set that all employers must report yearly to social security authorities and tax administration. The version available to researchers is provided by the INSEE. In particular, DADS contain information about all positions occupied by any worker in a specific year, with start and end date at the daily level. In particular, for each position held by one individual we observe: the occupation, the firm and sector, both location of work and residency and the number of hours spent. When using DADS to build municipality-level indicators we rely on the municpality of residency.

Daily Deaths Files ("Fichier des Décès Quotidiens") from INSEE record each death that occurred between January 1, 2018 and June 5, 2020. For each death, we observe information relative to the event (the date and municipality of death as well as a category about the place of death - hospital or clinic, home, care home, etc.) and the individual (*département* of residency, sex, date of birth). INSEE made these files available at a higher frequency during the covid-19 crisis, but this comes at the expense of some quality checks. The files are originally recorded by municipalities and then gradually added to the INSEE data sets, one cannot exclude that the files were incomplete by the time of our analysis although we updated them frequently (last update: June 30^{th}).
URL: https://www.insee.fr/fr/statistiques/4487854

DEFIS ("Dispositif d'Enquêtes sur les Formations et Itinéraires des Salariés") is a database produced by the Céreq. It comes from a survey led on 4,500 firms and 16,000 of their workers as of 2013. Firms with more than 10 workers are representative of the whole private sector, but smaller ones are only representative for some sub-sectors. In this paper, we use the survey led on workers in 2015. The question of interest relates to the frequency of on-the-job contacts with the public. It refers to the current job of workers who have not changed firm since 2013, and to the one of 2013 for workers who changed firm since then. URL: https://www.cereq.fr/en/data-access-lifelong-learning-and-vocational-training-surveys-defis-cvts-defis-employee

***Filosofi* database** (a French acronym for "Localised Disposable Income System"), 2014 version, contains a series of local measures on income and poverty. INSEE uses fiscal and social benefits data to compute these indicators at the municipality level. In particular, we are interested in the median standard of living of each municipality's inhabitants. The concept of *standard of living* corresponds to the household disposable income divided by consumption units (using the OECD scale), to account for the size of the household. URL: https://www.insee.fr/fr/metadonnees/source/operation/s1451/presentation

Population Censuses are used to compute a series of measures at the municipality level. Each year: (i) a fifth of municipalities with less than 10,000 inhabitants are covered by an exhaustive census and (ii) a sample of 8% of the population of municipalities with 10,000 or more inhabitants are surveyed. In-depth questions relative to economic activity and family structure of households are only available for about 20% of the households of municipalities under 10,000 inhabitants and about 40% of the households in the other municipalities (10,000 inhabitants or more). Analyses of in-depth questions cannot be done for municipalities with less than 2,000 inhabitants as samples get too small. We use INSEE annual population counts and both exhaustive and partial census data files.
URL: https://www.insee.fr/fr/information/2383265

Urban Areas are defined by the INSEE as a group of neighboring municipalities encompassing an urban centre and its periphery made of municipalities where at least 40% of employed inhabitants works in the urban centre, as of 2010. We often only consider the big urban areas, where the centre contained 10,000 jobs or more, as of 2010. Big urban areas represent 80% of the French mainland population in 2014.

C Appendix 3 - Additional Tables and Figures

1 Institutional framework

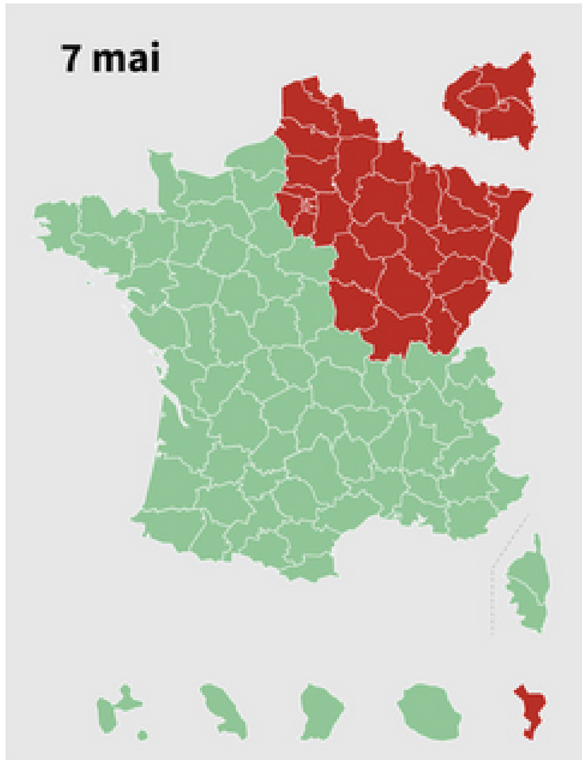


Figure A1: High- (red) and low-infection (green) *Départements* as of May 7, 2020

Note: Map of *Départements* issued by the Government on May 7, 2020. See source.

2 Descriptive statistics

Table A1: Distribution of the explanatory variable by poverty status

	All		Poor municipalities		Non-poor municipalities	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Share of over occupied housing units	.0175874	.0255011	.0328289	.0436706	.0160234	.0222453
Index of frequent contact	.5826732	.0360948	.5923971	.0413655	.581551	.0344396
Share of essential workers	.1942225	.0633863	.234419	.0569818	.1875544	.0554648
Share of multi-generational households	.0237836	.0113051	.0252773	.0112828	.0234873	.0112877
Observations	15093		1388		13431	

This table shows the distribution of the explanatory variables used in the analysis for the full sample and by poverty status. Poor municipalities are defined as belonging to the bottom 25% of the national median income distribution at the municipality level. The sample is restricted to municipalities within urban areas.

3 Association between poverty and occupation and housing variables

Table A2: Association between poverty and occupation and housing variables

	Index of frequent contact	Share of essential workers	Share of over-crowded housing
Panel A: All urban areas			
Main coefficient	0.48390***	0.90858***	2.46026***
	(0.16111)	(0.08658)	(0.25582)
Control outcome mean	0.092	0.092	0.091
Observations	14684	14684	14360
	Share of multi-generational hh with at least one worker		
Panel B: Urban areas with more than 2000 inhabitant cities			
Main coefficient	2.03794**		
	(0.79269)		
Control outcome mean	0.086		
Observations	3741		
Urban areas FE	✓	✓	✓
Controls	✓	✓	✓

** p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses are clustered at the département level.* Each column reports the result of a separate regression of poverty on each mechanism variable. Poor is defined as belonging to the first quartile of the median income distribution. Controls include total population and population over 65 years old. The control outcome mean line reports the mean of the poverty variable in low-infection *départements*.

4 Discussion of the occupational exposure measures

Table A3: Effect of Covid-19 on excess mortality - Occupational exposure

	Excess Mortality Rate, April 2020		
Infected Region=1 × Share of essential workers	0.97819*		0.62669
	(0.50663)		(0.48922)
Infected Region=1 × Index of frequent contact		2.56144***	2.12282***
		(0.81134)	(0.76049)
Urban areas FE	✓	✓	✓
Controls	✓	✓	✓
Control outcome mean	1.036	1.036	1.036
Adjusted R^2	0.0467	0.0469	0.0488
Observations	13471	13471	13471

* *p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses are clustered at the département level.* This table shows the result of regressing municipalities' excess mortality in April 2020 on a dummy indicating that the municipality is located in a high-infection *département*, a variable measuring occupational exposure and the interaction of these variables, using the ratio definition of excess mortality (i.e. number of deaths in April 2020 as compared to April 2018 and 2019). The first two columns examine the effect of being defined as an essential worker and of exercising a frequent contact occupation, separately. The last column includes both occupational exposure variables. All regressions include urban areas fixed-effects and control for total population and for the age structure in the municipality. The control outcome mean line reports the mean of the excess mortality rate in low-infection *départements*.

5 Oaxaca-Blinder decomposition

The top part of Table A4 reports the excess mortality rate in poor and non-poor municipalities in high-infection *départements*, as well as the share of the difference between both rates that is explained by the included variables, and the share that is unexplained. The middle and bottom parts of the table describe, respectively, the contribution of each variable to the explained and unexplained shares of the difference. The first column of Table A4 indicates that 77% of the 39 percentage points difference in excess mortality rate between rich and poor municipalities within urban area is explained by the variables capturing occupational exposure and housing conditions. The sole share of overcrowded housing contributes 84% of these 77%, while the essential worker variable explains the rest.[23] The inclusion of population controls in column (2) makes the explained share jump to virtually all of the total difference, but does not affect much the respective weight of each covariate.

[23]The essential worker variable contributes significantly to the explained share whereas Table A3 shows that most of the essential worker effect is absorbed by the contact channel. It suggests that being an essential worker explains to some extent the difference in excess mortality between poor and rich municipalities in high-infection areas. However, the frequency of social contact is the main determinant of the occupational exposure effect that explains differences in excess mortality.

Table A4: Oaxaca-Blinder decomposition of the excess mortality gap between poor and rich municipalities in high-infection areas

	Excess Mortality Rate, April 2020	
Very poor (Quart1) = 0	1.20117***	1.20117***
	(0.02015)	(0.02016)
Very poor (Quart1) = 1	1.59473***	1.59473***
	(0.06071)	(0.06091)
Difference	-0.39356***	-0.39356***
	(0.06397)	(0.06416)
Explained	-0.30314***	-0.41082***
	(0.03911)	(0.04738)
Unexplained	-0.09042	0.01726
	(0.06669)	(0.07215)
Explained		
Share of over occupied housing units	-0.25541***	-0.18438***
	(0.03143)	(0.02945)
Index of frequent contact	-0.00326	-0.00173
	(0.00294)	(0.00206)
Share of essential workers	-0.05203***	-0.04966***
	(0.01889)	(0.01880)
Urban Area, code	0.00756	0.00692
	(0.01147)	(0.01140)
Population Municipality, 2014		0.62253***
		(0.15872)
Pop. 65-74		-1.21409***
		(0.24892)
Pop. 75-84		0.11918
		(0.20209)
Pop. 85+		0.29042***
		(0.10711)
Unexplained		
Share of over occupied housing units	0.03890	-0.03834
	(0.03882)	(0.04820)
Index of frequent contact	0.00061	-0.00072
	(0.00536)	(0.00551)
Share of essential workers	-0.03340	-0.03391
	(0.02660)	(0.02688)
Urban Area, code	-0.02148	-0.02685
	(0.05280)	(0.05358)
Population Municipality, 2014		-0.63503**
		(0.25436)
Pop. 65-74		1.32260***
		(0.50608)
Pop. 75-84		-0.18966
		(0.46288)
Pop. 85+		-0.25624
		(0.23142)
Constant	-0.07506	-0.12459
	(0.08940)	(0.10127)
Observations	5341	5341

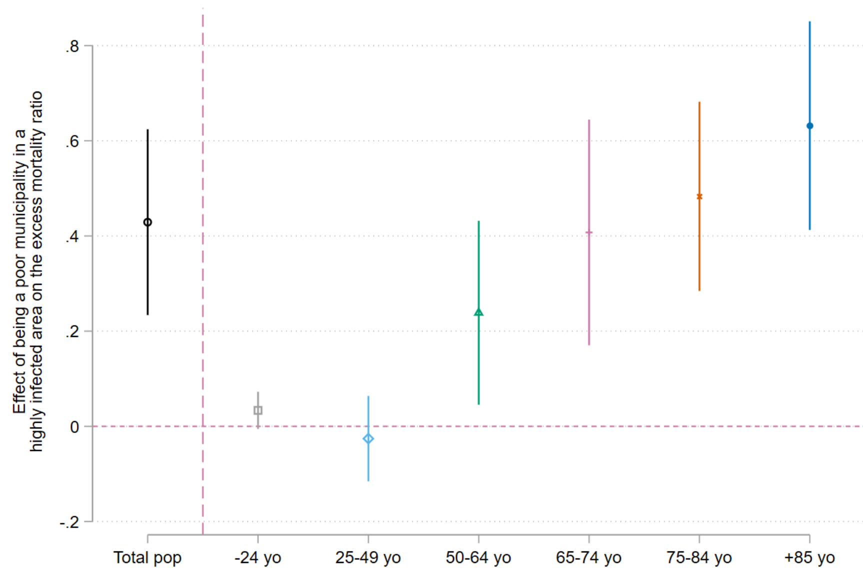
** p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses.* This table reports the output of a Oaxaca-Blinder decomposition (Oaxaca, 1973; Blinder, 1973) of the gap in excess mortality between rich and poor municipalities in high-infection areas. It indicates that the share of this gap that is explained by included covariates. Each covariate has been normalized.

6 Robustness checks

Excess mortality according to municipality's income by age group

Age is one of the main determinants of COVID-19 mortality (Wu and McGoogan, 2020): the National Public Health Agency, in its report of March 24, estimates the average age at death due to COVID-19 at 81.2. Therefore, we expect most of the variation in excess mortality to come from the top of the age distribution. Figure A2 of Appendix 6 shows the coefficient from the same triple-difference specification as in Table 1, for each age group separately. The coefficient for the total population is reproduced at the left hand side of Figure A2. We observe a pattern increasing with age: among people over 85 y.o., the difference in excess mortality between rich and poor municipalities within a given urban area is larger by 63 percentage points in high-infection *départments* than in low-infection ones. If the coefficients in the four top age groups are not significantly different from each other, they are significantly different from the coefficients for the population below 50 y.o. That supports our previous findings by showing that they are consistent with the empirical fact that most of COVID-19 related mortality is to be found among the elderly. It also indicates that the causal impact of poverty on COVID-19 related mortality is particularly strong for this age group.

Figure A2: Differential effect of Covid-19 in rich and poor municipalities by age group



NOTE: This graph plots the triple difference coefficient for each age group separately. It measures the effect of the interaction term between the high-infection region dummy and the poverty dummy on the excess mortality in April for each age group.

Alternative excess mortality measure

Our preferred excess mortality measure described in Section 2 allows to account for population size, and is in line with the recommendations of the National Public Health Institute. However, we reproduce the main specification of Table 1 on the number of deaths rather than on the excess mortality rate. Table A5 of Appendix 6 shows the triple-difference coefficients of a regression of the death toll in April on three dimensions (and their interactions): (i) living in a high- v.s. low-infection region; (ii) living in a poor v.s. rich municipality, (iii) in 2020 v.s. the average between 2019 and 2018. It indicates that, within urban areas in high-infection *départements*, being a poor municipality (i.e. belonging to the first quartile of the income distribution) increases the number of deaths in April 2020 by 9 units relative to a baseline number of deaths in rich municipalities during the pre-COVID period of 3.8. In low-infection *départements*, the average pre-COVID difference in death toll between rich and poor municipalities of the same urban area was about 1.6 units. It has only increased by 0.7 units after COVID-19. The main effect slightly decreases if we define poverty relative to the median of the income distribution, but remains in the same order of magnitude. Results are therefore consistent with our main specification, and are not sensitive to the definition of the outcome variable.

Table A5: Death toll in April according to municipalities' median income

	Death toll, April			
Infected Region=1	4.44356**	1.47092	4.43288**	1.43097
	(1.88259)	(0.95593)	(1.92102)	(0.97176)
Very poor (Quart1)=1	4.56109***	1.61709**		
	(0.80568)	(0.79419)		
Infected Region=1 × Very poor (Quart1)=1	3.50447**	0.86855		
	(1.34682)	(0.65567)		
2020=1	0.31417***	0.31417***	0.30775***	0.30775***
	(0.08710)	(0.08710)	(0.08374)	(0.08374)
Infected Region=1 × 2020=1	1.13961***	1.13961***	1.14070**	1.14070**
	(0.42557)	(0.42559)	(0.43813)	(0.43815)
Very poor (Quart1)=1 × 2020=1	0.41920*	0.41920*		
	(0.24234)	(0.24235)		
Infected Region=1 × Very poor (Quart1)=1 × 2020=1	4.62875**	4.62875**		
	(1.97916)	(1.97925)		
Poor=1			2.75368***	0.99277*
			(0.50238)	(0.51641)
Infected Region=1 × Poor=1			2.02596**	0.61896*
			(0.93545)	(0.32422)
Poor=1 × 2020=1			0.12968	0.12968
			(0.08445)	(0.08446)
Infected Region=1 × Poor=1 × 2020=1			1.68545**	1.68545**
			(0.82111)	(0.82115)
Urban areas FE	✓	✓	✓	✓
Controls	.	✓	.	✓
Control outcome mean	2.329	2.329	1.981	1.981
Observations	44457	44457	44457	44457

** p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses are clustered at the département level.* This table shows the result of regressing municipalities' death toll in April on a dummy indicating that the municipality is located in a high-infection region (*département*), a dummy indicating that the municipality's median income is under the poverty cut-off, a dummy *Post* equal to one in 2020, and the interaction of these dummies. The poverty cut-off in columns (1) and (2) corresponds to the first quartile of municipalities' median income, while it corresponds to the median of municipalities' median income in columns (3) and (4). All regressions include urban areas fixed-effects. Regressions in columns (2) and (4) further control for total population and for the age structure in the municipality.

D Appendix 4 - Mortality Over Time

1 Change in mortality over time

We perform our main analysis on the month of April 2020 (compared to April of 2018 and 2019). In this appendix we present results for other periods of 2020 with two main objectives: first to be transparent and comprehensive on the evolution of mortality over time (cf. 1.1), and second to show that focusing on April eases interpretation without loss of much information (cf. 1.2).

1.1 April as the peak in mortality

Figure A3 describes the evolution of the ratio of mortality 2020 vs. (the average of) 2018-2019 over time and within the four categories we compare (i.e. low vs. high infection areas and poorer vs. other municipalities). We compute the mortality ratio for periods of contiguous two weeks, from the weeks 1 and 2 to the weeks 21 and 22. Three main periods emerge from Figure A3: first, until weeks 9 and 10, the mortality of 2020 was slightly lesser than mortality in 2019 and 2018 (a fact explained by the strength of the 2018 Influenza epidemic in France); second, a sharp rise in mortality occurs from weeks 11 and 12; third, mortality seems to decline back to previous levels from weeks 17 and 18.

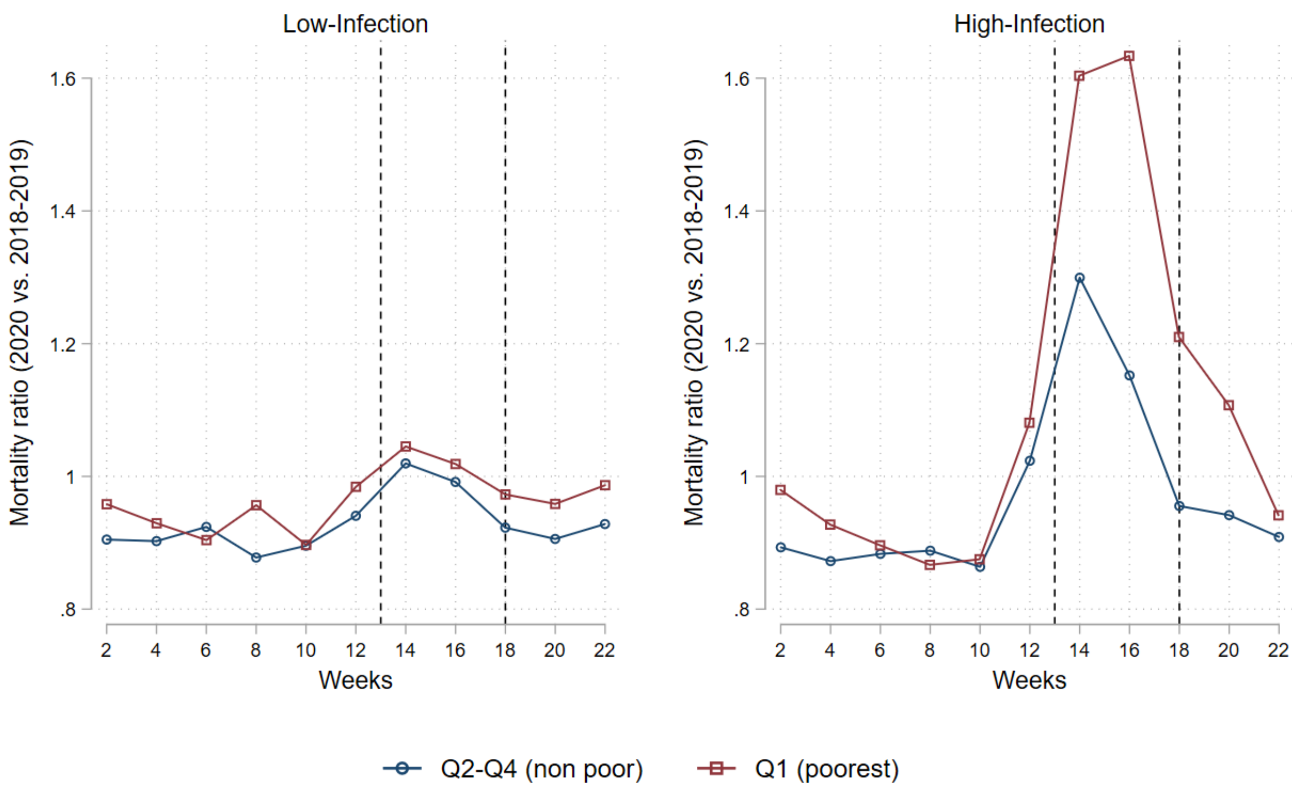
The main take-way from this exercise is that April (roughly from week 13 to 18, as indicated by the vertical black lines on the Figure) encompasses the peak of the 2020 rise in mortality. By selecting this month, we thus perform our main analysis on the weeks when COVID-19 was most salient in French mortality records.

1.2 Performing the analysis on other time periods

From Figure A3 it also appears strikingly that the pattern in mortality is much more pronounced in high-infection areas and disproportionately affect the poorest municipalities. Such observation is at the core of our main analysis.

Focusing on a month-to-month analysis has two main advantages: first, it eases the analysis by reducing the dimensions of the question and second, it makes the ratio of mortality more reliable (by reducing the number of municipalities with no death record over a specific time period). For the sake of completeness however, we estimate again our main models (that are based on Equation 1) at the 2-weeks-pair level. We report graphical evidence on the estimated coefficients below (in Figures A4 and A5) and tables or numbers are available upon request.

Figure A3: 2020 Excess Mortality, Over Weeks



Binscatter of Surmortality by pair of weeks.
Vertical black lines indicate the month of April.
Urban Area fixed-effects.
Controls: total population, population over 65

Our main take-away message here is that our model essentially performs well in the weeks around the peak of mortality. Coefficients in April are unsurprisingly and reassuringly the highest and most significant. If anything, this result confirms our interpretation of the main effect and the explored mechanisms.

Figure A4: Poverty Effect Over Time

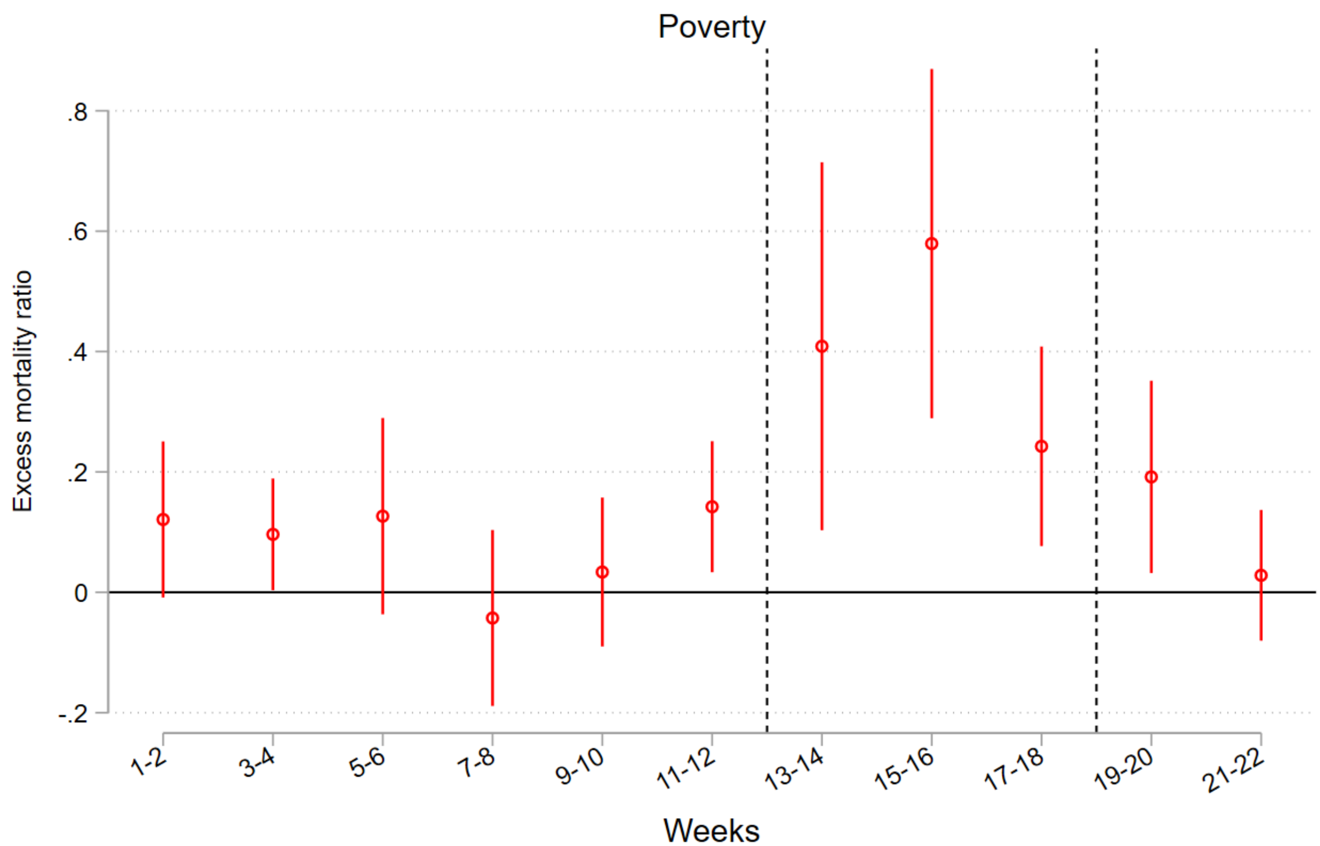
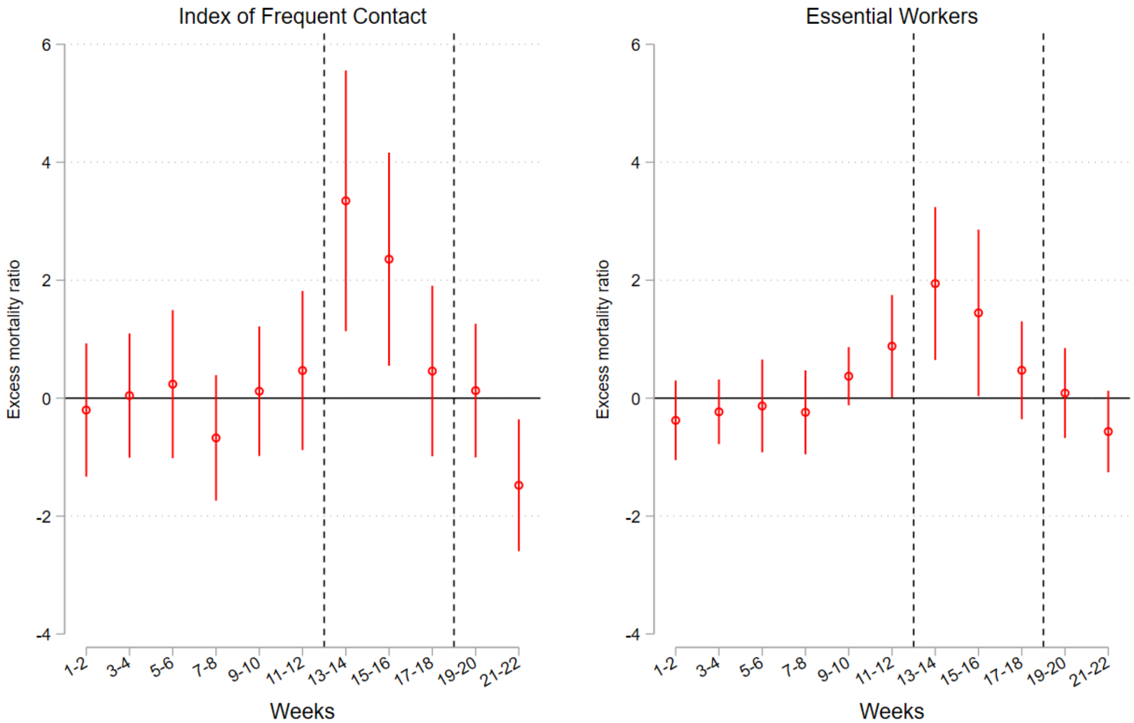
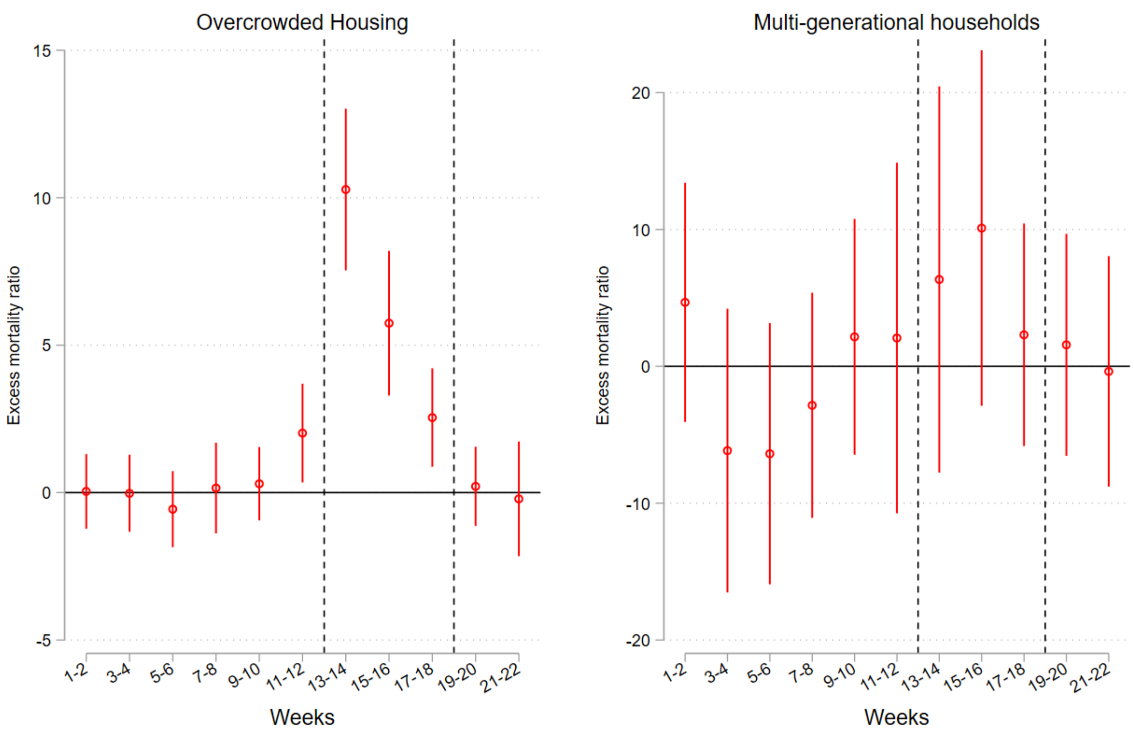


Figure A5: Mechanisms: Over Time Analyis



(a) Labor Market Conditions



(b) Housing Conditions

Issued in the series Discussion Papers 2019

2019

01/19 January, **Aline Bütikofer**, Christopher Cronin, Meghan Skira, "Employment Effects of Healthcare Policy: Evidence from the 2007 FDA Black Box Warning on Antidepressants"

02/19 February, **Ingar Haaland** and Cristopher Roth "Beliefs About Racial Discrimination and Support for Pro-Black Policies "

03/19 February, **Astrid Kunze** and Xingfei Liu, "Universal Childcare for the Youngest and the Maternal Labour Supply"

04/19 February, **Ingvild Almas, Alexander W. Cappelen, Bertil Tungodden**. "Cutthroat capitalism versus cuddly socialism: Are Americans more meritocratic and efficiency-seeking than Scandinavians?"

05/19 February**, Chang Koo Chi**, Kyoung Jin Choi. "Performance Measurement in Agency Models"

06/19 March, **Alexander W. Cappelen**, **Ranveig Falch** and **Bertil Tungodden.** "The Boy Crisis: Experimental Evidence on the Acceptance of Males Falling Behind"

07/19 March, Frode Skjeret, **Frode Steen** and **Timothy G.A Wyndham**. "Paywalls and the demand for online news"

08/19 April, **Ola. H. Grytten** and Viktoriia Koilo. "The Financial Instability Hypothesis and the Financial Crisis in Eastern European Emerging Economies"

09/19 April, **Alexander W. Cappelen**, Johanna Mollerstrom, Bjørn-Atle Reme and **Bertil Tungodden.** "A Meritocratic Origin of Egalitarian Behavior"

10/19 April, **Fanny Landaud**. "From Employment to Engagement? Stable Jobs, Temporary Jobs, and Cohabiting Relationships"

11/19 May, **Ola Honningdal Grytten** and Viktoriia Koilo. "Evidence of the Environmental Kuznets Curve in Emerging Eastern European Economies"

12/19 June, Rune Midjord, Tomás Rodríguez Barraquer, and **Justin Valasek.** "Robust Information Aggregation Through Voting"

13/19 June, Eva M. Berger, **Henning Hermes**, Guenther Koenig, Felix Schmidt, and Daniel Schunk. "Self-regulation Training and Job Search Behavior: A Natural Field Experiment Within an Active Labor Market Program"

14/19 June, **Henning Hermes**, Martin Huschens, Franz Rothlauf and Daniel Schunk. "Motivating Low-Achievers—Relative Performance Feedback in Primary Schools"

15/19 August, Viktoriia Koilo and Ola **Honningdal Grytten.** "The Blue Maritime C luster Crisis Financial Instability and Supply Chain Management Effects"

16/19 September, Jonas Andersson, **Fred Schroyen** and Gaute Torsvik. "The impact of international tax information exchange agreements on the use of tax amnesty: evidence from Norway"

17/19 September, Ingrid Kristine Folgerø, **Torfinn Harding** and Benjamin S. Westby. "Going Fast or Going Green? Evidence from Environmental Speed Limits in Norway"

18/19 September. Julie Riise, Barton Willage and **Alexander Willén.** "Can Female Doctors Cure the Gender STEMM Gap? Evidence from Randomly Assigned General Practitioners"

19/19 September**, Aline Bütikofer**, **Katrine V. Løken** and **Alexander Willén.** "Building Bridges and Widening Gaps: Efficiency Gains and Equity Concerns of Labor Market Expansions"

20/19 September, Richard Friberg, **Frode Steen** and **Simen A. Ulsaker**. "Hump-shaped cross-price effects and the extensive margin in cross-border shopping"

21/19 July, Mai Nguyen-Ones, and **Frode Steen. "**Market Power in Retail Gasoline Markets"

22/19 October, Tunç Durmaz and **Fred Schroyen.** "Evaluating Carbon Capture and Storage in a Climate Model with Endogenous Technical Change"

23/19 November, **Henning Hermes** and Daniel Schunk. "If You Could Read My Mind – An Experimental Beauty-Contest Game With Children"

24/19 December, **Vincent Somville.** "Having a Daughter Reduces Male Violence Against a Partner"

2020

01/20 January, **Laura Khoury**, Clément Brébion and Simon Briole. "Entitled to Leave: the impact of Unenployment Insurance Eligibility on Employment Duration and Job Quality"

02/20 January, Thomas Buser, **Alexander Cappelen**, Uri Gneezy, Moshe Hoffman and **Bertil Tungodden**. "Competitiveness, gender and handedness: a large-sample intercultural study"

03/20 February, **Patrick Bennett**, Chiara Ravetti and Po Yin Wong. "Losing in a Boom: Long-term Consequences of a Local Economic Shock for Female Labour Market Outcomes"

04/20 April, **Øivind A. Nilsen**. "The Labor Market in Norway: 2000-2018"

05/20 April, **Simen A. Ulsaker**. "Exclusionary contracts and incentives to innovate"

06/20 May, **Alexander W. Cappelen**, **Ranveig Falch**, **Erik Ø. Sørensen** and **Bertil Tungodden**. "Solidarity and Fairness in Times of Crisis"

07/20 May, Gozde Corekcioglu, Marco Francesconi and **Astrid Kunze**. "Do Generous Parental Leave Policies Help Top Female Earners?"

08/20 June, **Ola Honningdal Grytten**. "Weber revisited: A literature review on the possible Link between Protestantism, Entrepreneurship and Economic Growth"

09/20 June, Eva M. Berger , Ernst Fehr, **Henning Hermes** , Daniel Schunk and Kirsten Winkel. "The Impact of Working Memory Training on Children's Cognitive and Noncognitive Skills"

10/20 June, **Ola Honningdal Grytten**. "Two centuries of economic growth: Norwegian GDP 1816-2020"

11/20 July, **Ola Honningdal Grytten**, Magnus Lindmark and Kjell Bjørn Minde. "Energy Intensity and the Environmental Kuznets Curve"

12/20 August, Ola Honningdal Grytten. "Puritan Motivation for Serial Entrepreneurship: The Haugean Example"

13/20 August, Julian Johnsen, Hyejin Ku and **Kjell G. Salvanes**. "Competition and Career Advancement: The Hidden Costs of Paid Leave"

14/20 August, Patrick Bennett, Richard Blundell and **Kjell G. Salvanes**. "A Second Chance? Labor Market Returns to Adult Education Using School Reforms"

15/20 August, Paul Brandily, Clément Brébion, Simon Briole and **Laura Khoury**. "A Poorly Understood Disease? The Unequal Distribution of Excess Mortality Due to COVID-19 Across French Municipalities"

NHH

NORGES HANDELSHØYSKOLE
Norwegian School of Economics

Helleveien 30
NO-5045 Bergen
Norway

T +47 55 95 90 00
E nhh.postmottak@nhh.no
W www.nhh.no