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Trusting the Health System and COVID 19 Restriction Compliance

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ABSTRACT

We examine the extent to which exposure to higher relative COVID-19 mortality (RM), influences health system trust (HST), and whether changes in HST explain the perceived ease of compliance with pandemic restrictions during the COVID-19 pandemic. Drawing on evidence from two representative surveys covering all regions of 28 European countries before and after the first COVID-19 wave and using a difference in differences strategy together with Coarsened Exact Matching (CEM), we document that living in a region with higher RM during the first wave of the pandemic increased HST. However, the positive effect of RM on HST is driven by individuals over 45 years of age, and the opposite effect is found among younger cohorts. Futhermore, we find that a higher HST reduces the costs of complying with COVID-19 restrictions, but only so long as excess mortality does not exceed the average by more than 20%, at which point the ease of complying with COVID-19 restrictions significantly declines, offsetting the positive effect of trust in the healthcare system. Our interpretation of these estimates is that a higher RM is interpreted as a risk signal among those over 45, and as a signal of health-care system failure among younger age individuals.

1. Introduction

Given that clinical processes and health care decisions are complex and poorly understood by the public, users' trust can serve as a behavioural resource to navigate the health system. People's beliefs about the efficacy and effectiveness of health care services can be critical for decision making in a crowded healthcare system (Ramalingam et al., 2020).[2] Nonetheless, under pandemic circumstances like those of the COVID-19 pandemic, cooperation with pandemic regulations depends heavily on people's goodwill. As a result, health system trust (HST) becomes a low-cost heuristic for users deciding whether or not to comply with COVID-19 restrictions and treatment compliance (O'Malley et al., 2004; Ozawa and Sripad, 2013, 1997; Voeten et al., 2009; van der Weerd et al., 2011). According to Hall et al. (2001), HST refers to a person's belief that healthcare institutions and professionals in general are concerned about their health. However, it is commonly founded on normative value judgements derived from knowledge of other people's experiences and information disseminated through the media, rather than solely on personal experience (Thiessen, 2009).[3]

In a pandemic, HST can influence the perceived cost of compliance with social distancing (Bargain and Aminjonov, 2020; Clark et al., 2020),[4] as well as the individual's likelihood of reporting a positive test, and more generally, adhering to self-isolation or quarantine requirements (Gilson, 2003; Department for International Development,

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[2] In extreme cases, excess reliance on trust can crowd out preventive healthcare behaviours Including skipping breast and cervical cancer screenings (Yang et al., 2011), reducing contact with doctors (Trachtenberg et al., 2005; LaVesit et al., 2009), or disregarding medical advice (Egede and Ellis, 2008).

[3] According to Zengh et al. (2003) trust can be explained by four dimensions (both inter-personal and public): (i) *fidelity,* or upholding the patient's interests above all else, (ii) *competence,* or ability to produce the best possible outcomes, (iii) *honesty*, avoiding deliberate misrepresentation, and (iv) c*onfidentiality,* or the correct use of sensitive information.

[4] Similarly, some studies establish an association between institutional trust and ease of compliance with recommendations in the context of the H1N1 epidemic in the UK (Rubin et al., 2009) and Italy (Prati et al., 2011), SARS in Hong Kong (Tang and Wong, 2003) and Ebola in Liberia (Morse et al., 2016). Relatedly, lack of trust in health institutions is associated with increased difficulties in dealing with bioterrorism threats (Meredith et al. 2007; McKee and Coker, 2009).

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2020). COVID-19 entailed the implementation of historically unprecedented interventions limiting individuals' freedoms.[5] However, so far, we know little about how does the severity of a pandemic influence HST. To date, it is unclear how individuals interpret changes in a country's relative COVID-19 mortality, whether as a signal of higher risk exposure calling for further healthcare system protection, or a sign of failure of the health system regulations to stop the pandemic.

This paper adds to the literature by shedding light on how HST changes with the exposure to higher COVID-19 mortality, which was a piece of information heavily communicated in the media. Furthermore, we attempt to disentangle whether RM is interpreted as a proxy of further risk exposure, or health system failure. Next, we examine whether changes in HST influence individuals' perceived ease of compliance with lockdown restrictions.[6] We exploit evidence from two representative survey datasets from 28 European countries from before and after the first wave of the pandemic, as well as regional level NUTS-2[7] mortality data. We use a difference-in-difference strategy combined with Coarsened Exact Matching (CEM); a matching methodology developed by Iacus et al. (2012)[8] We document that RM increased health system trust (HST), though the effect differs across age groups. HST reduces the costs to comply with COVID-19 restrictions so long as mortality does not exceed 20% of the average excess mortality for the period, after which the ease of compliance with the COVID-19 restrictions markedly declines, thus offsetting the positive effect of RM on HST.

We structure the article as follows. Section 2 reports the related literature on HST and especially, how it impacts health care decision making. Section 3 presents the data used and the variable construction. Next, in Section 4 we discuss the empirical strategy, results are reported in Section 5, and finally, Section 6 offers the main conclusions.

2. Related literature

2.1. Healthcare system trust and outcomes

Given the importance of sound health advice, vulnerable people take for granted that doctors and, by extension, other medical professionals are more knowledgeable than they are, and trust their judgement (Parsons, 1951).[9] However, when health care expectations are not met (e.g., when mortality keeps growing in a pandemic), trust can be abruptly shattered (Mechanic, 1998), and feelings of betrayal or outrage can inhibit HST (Baier, 1986). Consistently, previous evidence documents a relationship between poorer self-rated health status and lower trust in the healthcare system (Armstrong et al., 2006; Mohseni and Lindström, 2007). The latter might be explained by the higher adherence to treatment of trusting patients, which results in improvements in peoples health status. Hence, the attainment of higher patient satisfaction, successful care continuity, and medication adherence depends on the health system's ability to be trusted (Thom et al., 1999). However, it is an empirical question whether HST played a similar role in an unexpected pandemic, as experience plays a different role, especially during the exceptional circumstances of the first wave of the COVID-19 pandemic.

2.2. Health system trust and pandemics

In a pandemic, people's compliance with self-protective measures is driven by both risk perceptions (de Zwart et al., 2007; Leppin and Aro, 2009),[10] and the perceived effectiveness of governments and their health systems (de Zwart et al., 2009, Blendon et al., 2008). Evidence from previous pandemics suggest a consistent story. Winters et al. (2020) document that more prudent people tend to rely more on HST. Similarly, during the H1N1 pandemic, protective behaviours and vaccination intentions were associted to trust in health authorities (Freimuth et al., 2014; Chuang et al., 2015).

Dryhurst et al. (2020) document that trust in government and science influences individuals perceived risk of COVID-19.[11] Consistently, in an analysis of 27 European countries following the first wave of COVID-19, Beller et al. (2022) found that trust in the health care system plummeted among people with unmet health needs and higher levels of mental distress, for example those who were economically vulnerable and had higher levels of loneliness. In contrast, happier and healthier individuals were more likely to trust China's healthcare system, according to Zhao et al. (2019). As a result, the impact of risk perceptions in the face of a health threat can be a double-edged sword. Wheareas some individuals may change their behaviour if they believe they can manage the threat of COVID-19, the opposite might be true if they believe they are helpless in facing the threat (Witte and Allen, 2000).

Some research has examined the influence of HST in the context of COVID-19. Eichengreen et al. (2021) studied the effect of exposure to a pandemic on young people in 138 countries, and document a significant reduction in trust in scientists. They then document that distrust caused by COVID-19 reduced their compliance with health recommendations and led to lower rates of childhood vaccination. Consistently, Chan et al. (2020) finds that regions with higher trust in the healthcare system are more likely to exhibit mobility reductions once the government orders citizens to stay at home except for essential travel, compared to regions with lower healthcare system trust.[12] A number of studies show that increased trust in public institutions has been found to increase compliance with policy constraints, such as social distancing (Lalot et al., 2022).[13] However, all these studies focus on the effects of trust rather than on whether the pandemic influenced health system choices.

While previous research has focused on the relationship between

[5] These include the effects on loneliness, unemployment, educational interruption, and interrupted healthcare, especially undeserved individuals. Indeed, some evidence suggests that whist early spring 2020 lockdown in Europe and the United States reduced mortality by 10.7%, later lockdowns did not (Herby et al., 2021).

[6] We do not assume that COVID − 19 exposure is a risk for everyone, but for the average individual. For instance, it might well be that younger people exposure might develop natural immunity and are thereby better able to protect the vulnerable people the interact with. However, this is not the case for most of the population.

[7] The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU and the UK. The NUTS-2 classification refers to basic regions for the application of regional policies. Background - NUTS - Nomenclature of territorial units for statistics - Eurostat (europa.eu)

[8] We attempt to improve over existing matching approaches in estimating causal inference by reducing any imbalance in covariates between treated and control units. CEM incorporates exact matching properties, but it allows the balance between treated and control groups to be chosen ex-ante rather than having to be discovered ex-post. This is the first study to use the CEM to estimate the effect of COVID-19 mortality on trust in healthcare.

[9] Consistently, some evidence documents that people with chronic conditions typically have a longer history of interactions with the healthcare system, but they also frequently have higher levels of resilience to setbacks (Hall et al., 2001).

[10] Consistently, the World Health Organization's risk communication guidelines state that "risk perception is the primary predictor of disaster prevention and mitigation behaviours."

[11] Elgar et al. (2020) civic engagement and confidence in state institutions are found to be negatively related to actual COVID-19 mortality.

[12] However, Algan et al. (2021) document that trust in scientists was the most important factor for ease of compliance with distancing measures, while government trust exerted a more ambiguous effect

[13] For example, Thornton (2022) documents that if citizens' trust with the health system had been the same as their trust in government, the infection rate would have been 13% lower.

compliance and trusts in institutions (Brodeur et al., 2021; Bargain and Aminjonov, 2020; Sarracino et al., 2022), this paper examines the effect of relate COVID-19 mortality on HST and its subsequent effect on lockdown compliance.[14] The remainder of the paper reports the empirical strategy and results retrieved.

3. Data and methods

3.1. Data

The data used is the paper comes from two Eurobarometer (EB) survey datasets, more specifically the EB80.2, conducted between November and December 2013 before the COVID-19 pandemic, and the EB93.1, completed between July and August 2020, which provide us with two different cross-sections. Eurobarometer surveys are conducted on behalf of the European Commission and are commissioned by the Directorate-General Communication. The regular sample size (in the sense of completed interviews) is approximately 1000 respondents per country, except the United Kingdom (1300), Germany (1000), and Luxembourg, Cyprus and Malta with 500 interviews each. In the following analysis post-stratification weights will be used. These weights adjust each sample in proportion to its share in the total population aged 15 and over of the European Union based on population figures published by EUROSTAT in the Regional Statistics Yearbook.

The EB80.2 interviewed face to face 27,919 individuals living in the EU-28, whereas the EB93.1 interviewed 33,059 citizens living in the EU-27 and United Kingdom (UK).[15] All respondents were residents in the respective country aged 15 and over. The final sample contains only individuals living in EU-27 and UK, aged 18 years and older (Total: 55,371 observations; 27,374 observations for EB80.2 and 27,997 observations for EB93.1). (See Table A1 for detailed description of the initial sample by country).

3.2. Dependent variables

We define two dependent variables, namely HST and ease of compliance with lockdown measures. HST is measured as follows: "*Please, tell me if you tend to trust or not to trust overall healthcare in your country: (1) completely trust, (2) somewhat trust, (3) somewhat mistrust and (4) completely mistrust*". We define the variable "*trust in the healthcare system*" (HST) inverting the Likert scale of the survey so that (1) corresponds to "*totally mistrust*" and (4) to "*totally trust*".

The variable ease of compliance with lockdown restrictions is measured using the following question: "*Thinking about the measures taken to fight against the Coronavirus outbreak, in particular the lockdown measures, would you say that it was an experience easy or difficult to cope with?: (1) very easy to cope with, and even an improvement to your daily life", (2) fairly easy to cope with, (3) both easy and difficult to cope with, (4) fairly difficult to cope with, (5) very difficult to cope with, and even endangering your mental and health*". We define the variable "*ease of compliance with lockdown restrictions*" (COMPLY) inverting the Likert scale, so that (5) corresponds to "*very easy to cope with*" and (1) corresponds to "*very difficult to cope with*".

3.3. Explanatory variables

Based on the previous literature (Listhaug and Jakobsen, 2017; Newton et al., 2017) we include controls for age, gender, nationality, marital status, occupation, age when finishing full-time education, household composition, difficulties in paying bills, level in society and Internet use. In addition, country-specific data includes controls for the size of the municipality and the region of residence. Although we lack specific information on income and wealth, we have information on the perceived difficulty to pay bills and their perceived self-reported social status. Descriptive statistics are shown on Table A3. Furthermore, Eurobarometer data does not collect information on the full composition of the household, beyond dependents under 15, hence we can't identify the presence of older individuals in the household. We also do not have information on self-reported health status or whether they suffer from any chronic disease.

We draw on regional data on COVID-19 excess mortality, measured as the excess mortality in 2013 and in 2020 with respect to the average of 2016–2019, considering the average 14-day case rate of new COVID-19 cases per 100,000 inhabitants.[16] In the field of environmental pollution, a positive relationship has been documented between the risk perception of individuals exposed to pollution and local mortality records (Interdonato et al., 2014; Janmaimool and Watanabe, 2014; Wachinger et al., 2013). Although pollution affects people far more equally than COVID-19 and is more visible to individuals, the reporting on individual COVID-19 cases and deaths made the pandemic more visible, and it was presented as if the risk could affect everyone.

Relative mortality in 2013 ($RM_{2013,Nut}$) is computed using registered weekly deaths (all causes) during 2013 in each territorial units (NUTS-2) with respect to average deaths between 2016 and 2019, using information from Eurostat,[17] which allows to identify regions with excess mortality if $RM_{2013,Nut} \geq 0$.

$$Relativemortality2013_{Nut} = \frac{Deaths_{2013,Nut}}{\sum_{y=2016}^{2019} Deaths_{y,Nut} \Big/ 4} - 1 \tag{1}$$

Relative mortality in 2020 ($RM_{2020,Nut}$) is computed using average weekly registered deaths (all causes) between week 11 ($W_{11-2020}$) and week when respondent was interviewed ($W_{EB93.1}$) with respect to average weekly deaths between years 2016 and 2019 in each NUTS-2. The variable provides an estimate community deaths directly or indirectly attributed to COVID-19.

$$Averageweeklydeaths2016-19_{Nut} = \frac{\sum_{y=2016}^{2019} Deaths_{y,Nut}}{4 \bullet 52.14} \tag{2}$$

$$Relativemortality2020_{Nut} = \frac{\frac{\sum_{i=W_{11-2020}}^{W_{EB93.1}} Deaths_{w,Nut}}{W_{EB93.1}-W_{11-2020}}}{Averageweeklydeaths_{2016-2019,Nut}} - 1 \tag{3}$$

The variable *average cases* is defined as the average of 14-day case rate of newly reported COVID-19 cases per 100,000 population by week and territorial units ($14days\ cases_{w,Nut}$) between week 11 ($W_{11-2020}$) and the week when the respondent was interviewed ($W_{EB93.1}$). The sources consulted to compute the "Average Case Rate" by NUTS-2 are listed on Table B2.

[14] According to Plohl and Musil (2021), trust in science (medicine) predict the degree of compliance with restriction regulations, whereas other variables (religiosity, political leaning, curiosity about science) predict compliance through trust in science.

[15] It also included interviews for candidate countries (Albania, Macedonia, Montenegro, Serbia and Turkey) which were not considered for the purpose of this paper

[16] These measures have been calculated with reference to the region of residence (NUTS-2) except for Cyprus, Estonia, Latvia, Lithuania, Luxembourg and Malta for which the country as a whole has been taken as a reference. In total, regional information is available for 197 NUTS-2 and 6 countries.

[17] We cannot confirm that the information reported in the press coincides exactly with that appearing in these databases, but we have found that the countries used in this work meet the criteria of reliability and absence of manipulation examined in several studies (Sambridge and Jackson, 2020; Farhadi, 2021; Farhadi and Lahooti, 2021).

Table 1
The effect of relative mortality and age cohort exposure on health system trust (HST) – Difference in differences (DiD) and triple differences (DiDiD) estimates.

Dependent variable: HST	RM_t binary variable			RM_t continuous variable		
	M1	**M2**	**M3**	**M4**	**M5**	**M6**
	DiD Age·$Year_{2020}$	**DiD$RM_t Year_{2020}$**	**DiDiD**	**DiD Age·$Year_{2020}$**	**DiD$RM_t Year_{2020}$**	**DiDiD**
Relative Mortality (RM_t)	-0.0081 * **	-0.0079 * **	-0.0077 * **	-0.0464 * **	-0.0474 * **	-0.0658 * **
	(0.0005)	(0.0014)	(0.0032)	(0.0091)	(0.0150)	(0.0327)
	-0.2893	**-0.2822**	**-0.2751**	**-0.0005**	**-0.0008**	**-0.0025**
Age 31–45	-0.0074	-0.0155	-0.0121	-0.0077	-0.0171	-0.0129
	(0.0170)	(0.0121)	(0.0150)	(0.0170)	(0.0122)	(0.0170)
	-0.2643	**-0.5551**	**-0.4329**	**-0.2751**	**-0.6128**	**-0.4616**
Age 46–64	0.0608 * **	0.0865 * **	0.1745 * **	0.0606 * **	0.0866 * **	0.1759 * **
	(0.0160)	(0.0113)	(0.0794)	(0.0160)	(0.0113)	(0.0760)
	2.2125	**3.1722**	**6.5899**	**2.2051**	**3.1760**	**6.6456**
Age 65 +	0.2038 * **	0.2320 * **	0.2618 * **	0.2049 * **	0.2329 * **	0.2672 * **
	(0.0170)	(0.0118)	(0.0425)	(0.0170)	(0.0119)	(0.0468)
	7.7698	**8.9257**	**10.1651**	**7.8147**	**8.9631**	**10.3936**
$Year_{2020}$	0.0732 * **	0.1497 * **	0.1657 * **	0.0796 * **	0.1451 * **	0.1699 * **
	(0.0194)	(0.0413)	(0.0334)	(0.0195)	(0.0400)	(0.0353)
	2.6716	**5.6087**	**6.2385**	**2.9119**	**5.4276**	**6.4059**
Age 31–45·$Year_{2020}$	0.0491 * *		0.0511 * **	0.0522 * **		0.0581 * **
	(0.0245)		(0.0213)	(0.0245)		(0.0226)
	1.7427 * **		**1.8533**	**1.8939**		**2.1123**
Age 46–64·$Year_{2020}$	0.0834		0.0809 * **	0.0841 * **		0.0866 * **
	(0.0229)		(0.0230)	(0.0229)		(0.0206)
	3.0551 * **		**2.9608**	**3.0815**		**3.1760**
Age 65 + ·$Year_{2020}$	0.1506		0.1633 * **	0.1576 * **		0.1644 * **
	(0.0541)		(0.0373)	(0.0541)		(0.0320)
	5.9208		**6.1430**	**5.9208**		**6.1868**
RM_t·$Year_{2020}$		-0.0479 * **	-0.0468 * **		-0.4579 * **	-0.4534 * **
		(0.0023)	(0.0022)		(0.0302)	(0.0302)
		-1.7353	**-1.7272**		**-0.0508**	**-0.0501**
Age 31–45·RM_t			0.0050			0.0430 * **
			(0.0042)			(0.0142)
			-0.1784			**-0.0007**
Age 46–64·RM_t			0.0158 * **			-0.0392 * **
			(0.0039)			(0.0119)
			-0.5660			**-0.0005**
Age 65 +·RM_t			0.0250 * **			-0.0313 * *
			(0.0042)			(0.0168)
			-0.2034			**0.0028**
Age 31–45·RM_t·$Year_{2020}$			0.0057			0.0421
			(0.0045)			(0.0580)
			-0.8984			**-0.0006**
Age 46–64·RM_t·$Year_{2020}$			0.0217			0.1611 * **
			(0.0042)			(0.0545)
			0.7789			**0.0101**
Age 65 +·RM_t·$Year_{2020}$			0.0275 * **			0.1711 * **
			0.0045)			(0.0591)
			0.9891			**0.0117**
Intercept	3.6106 * **	3.5571 * **	2.3055 * **	2.7857 * **	2.7627 * **	2.7885 * **
	(0.0476)	(0.1314)	(0.3060)	(0.0132)	(0.0101)	(0.0131)
N	51,861	51,861	51,861	51,861	51,861	51,861
R^2	0.2176	0.2175	0.2187	0.0122	0.2125	0.2135
F	1287.96	1797.98	1937.20	884.15	1224.51	1686.29

Note: The table reports estimate of a canonical and a triple difference in differences specification examining the effect of relative mortality and age cohorts on health system trust (HST). We report in bold under the standard error coefficient in brackets report the effect of one standard deviation increase over dependent variable for continuous regressors or percentage increase over average dependent variable for binary regressors. The estimations have been performed using the final sample after CEM.All regressions include as explanatory variables: sex, marital status, years of education, nationality, economic activity, household size, number of household members (aged 15 and older, between 10 and 14 years, less 10 years), size of municipality of residence, difficulties for making ends meet, having internet at home, self-reported social class, territorial unit. Robust standard errors are clustered at NUTS-2 level. Models M1, M2 and M3 measure RM as a continuous variable in year t (t = 2013, 2020) with respect to average 2016–2019. Models M4, M5 and M6 measure RM as a binary variable: 1 if $RM_t > 0$ and 0 otherwise. Bold figures correspond to the effect of one standard deviation increase of the regressor over the dependent variable (for continuous variables) or the percentage variation with respect to the mean (for binary variables) Standard deviations in brackets. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$

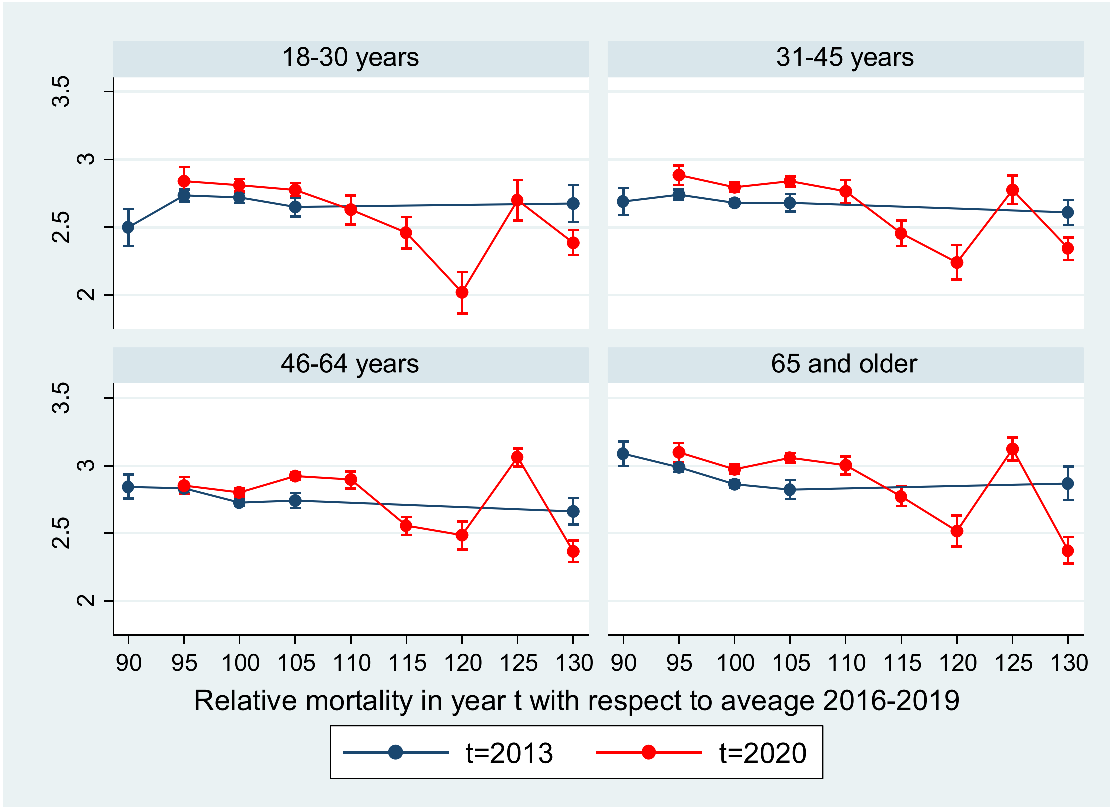

Fig. 1. Predicted trust in healthcare system after estimation of DiDiD model (model M6 of Table 1). Estimations have been performed using the final sample after CEM. Predicted trust in healthcare system after estimating a DiDiD model with interactions between age cohort, year 2020 and relative mortality with respect to average 2016–2019, and the following explanatory variables: sex, marital status, years of education, nationality, relation with economic activity, household size, number of household members (aged 15 and older, between 10 and 14 year, less 10 years), size of municipality of residence, difficulties for making ends meet, having internet at home, self-reported social class, territorial unit. Robust standard errors clustered at NUTS-2 level.

$$Averagecaserate_{Nut} = \frac{\sum_{i=W_{11-2020}}^{W_{EB93.1}} 14days - Cases_{w,Nut}}{W_{EB93.1} - W_{11-2020}} \tag{4}$$

$$14 - dayscases_{w,Nut} = \sum_{day=1}^{14} \frac{cases_{day,Nut}}{14}$$

Fig. A1 shows the relationship between relative mortality (RM) in 2013 and 2020 by NUTS-2. 54.55% of the territorial units exhibit a $RM_{2013} \leq 0$ and $RM_{2020} > 0$, but only 1.6% exhibit a $RM_{2013} \leq 0$ and $RM_{2020} > 0$. Table B1 displays the RM in 2013 and 2020 with respect to the 2013-16 average, the average case rate of newly reported COVID-19 cases, trust in healthcare (2013 and 2020) and perceived ease of compliance with restrictions (2020) by NUTS-2. Fig. A2 in the appendix shows a map of European territorial units shaded in red according to RM in 2020 with respect to the 2016–2019 average (higher intensity indicates higher RM), which suggests an association between lower regional RM and higher trust in the healthcare system.[18] Similarly, Fig. A3 displays the relationship between ease of compliance with lockdown restrictions and trust in the healthcare, suggesting an association between a region's healthcare system trust and ease of compliance with restrictions.[19] Finally, Fig. A4 in the appendix maps the spatial distribution of the perceived ease of compliance with lockdown restrictions and the average number of COVID-19 cases per 100,000 inhabitants and displays that in regions with a higher incidence rate, there is greater dispersion in ease of compliance with restrictions.[20]

[18] Regions with the highest RM are Madrid (Spain; 170.94), Lombardy (Italy; 153.03), Castilla La Mancha (Spain; 151.63) and London (United Kingdom; 135.43). In these regions, the lowest trust in the healthcare system is observed in London (2.06) and Madrid (2.34), which is 26.43% and 16.43% lower than the average confidence for all regions. On the other hand, in the regions with lower relative mortality there is a high concentration of Hungarian regions (Del-Alfold, Kozep-Dunantul, Kozep-Magyarorszag, Nyugat-Dunantul), which also show a degree of trust in the healthcare system around 7% higher than the average.

[19] Regions showing the greatest ease of compliance with mobility restrictions are Danish (Sjaelland (3.76), Syddanmark (3.68), Nordjylland (3.65) and Hovedstaden (3.64)). Malta (3.61), Overijssel (3.53) and Zeeland (3.50) in the Netherlands also stand out. In these regions, confidence in the healthcare system is well above average (32% in the Danish regions, 29% in Malta, 25% in the Dutch regions). In contrast, the greatest difficulties are concentrated in Cantabria (Spain; 1.33) and several Italian regions (Marche, 1.71; Toscana, 1.73; Liguria, 1.87). In these regions, trust in the healthcare system is well below average (52% in Cantabria and 39% in the Italian regions).

[20] The highest average number of confirmed cases per 100,000 inhabitants corresponds to several Spanish regions (Aragon, 168.10; Madrid, 132.87, La Rioja, 117.60) and Smalland Med Arna (Sweden, 119.69). In these regions, the ease of compliance with the restrictions is above average, except in Madrid where it is 6% below average. In contrast, the lowest average infection rate is observed in Northern Ireland (2.17), Scoltland (2.18) and Pohjois-ta Ita-Suomi (Finland, 2.49). In these regions, the ease of compliance with restrictions is above average (13%, 11% and 28%, respectively).

4. Empirical strategy

4.1. Exposure to COVID-19 and healthcare system trust

COVID-19 may have been a one-of-a-kind pandemic in terms of risk information exposure. Indeed, since the outbreak of the pandemic, the media has played a critical role in reporting on cases and deaths (Anwar et al., 2020; Tsao et al., 2021). Hence, one way to capture the effects of the exposure to the pandemic is by examining the effects of regional (excess) mortality in 2020 compared to the time periods immediately before the pandemic (2016–2019). We hypothesise that individuals' trust in the healthcare system may be affected by relative mortality (RM). However, we will examine the heterogenous exposure to the pandemic by an individual's age of the respondent.

To assess the impact of the pandemic on HST, we propose a difference-in-difference-in-differences toguether with a triple difference (DiDiD) specification, which compares trust in regions with excess mortality compared to all other regions, and in 2013 compared to 2020. A DiDiD model addresses the potential endogeneity coming form three types of unmeasured confounders: those that vary over time but affect people in a similar fashion (e.g., changes in the healthcare system between 2013 and 2020), those that vary across people but remain constant over time (e.g., fundamental differences among age cohorts), and finally, those that vary over time but affect people differently (e.g., mortality).

The DiDiD specification allows for differential trends across regions and by respondent's age. Following this assumption, we estimate the following DiDiD equation using ordinary least squares (OLS):

$$\begin{aligned} HST_{irct} = {} & \alpha_0 + \alpha_1 Age_{irct} + \alpha_2 RM_{rct} + \alpha_3 POST_t \\ & + + \alpha_4 Age_{irct} POST_t + \alpha_5 RM_{rct} POST_t \\ & + \alpha_6 Age_{irct} RM_{rct} + \alpha_7 Age_{irct} RM_{rct} POST_t \\ & + \gamma' X_{irct} + \delta_r + \nu_c + \varepsilon_{irct} \end{aligned} \tag{5}$$

where HST_{irct} is the level of trust in healthcare system (measured using a Likert scale, ranging from the value of 4 when respondents state that thay "*totally trust the health system*" to 1 when they state that they "*totally mistrust the health system*"). The data refers to an individual i living in region r and country c who is interviewed on year t. Age_{irct} depicts the age cohort of each individual as follows: 18–30 (omitted category), 31–45, 46–64 and 65 and older. Finally, RM_{rct} depicts the relative mortality of region r in year t (2013, 2020) compared to the average mortality in the period 2016–2019. We define RM as a *binary variable*, that either takes the value 1 if RM in that region and year is positive, or refers to a *continuous variable*, measuring higher excess mortality in each region and time period.

$POST_t$ refer to an indicator variable equal to 1 if the individual is interviewed during the pandemic in 2020 (0 if interviewed in 2013), and the vector X_{irct} measures a series of controls including gender, nationality, marital status, economic activity, age when stopped full-time education, household composition, having internet at home, difficulties in paying bills, self-perceived socio-economic status and internet use. Finally, δ_r and ν_c denote regional and country fixed effects. They capture long-term NUTS-specific differences and country invariant effects (e.g., those linked to the economic cycle). Robust standard errors are estimates after clustering the data at the regional level.[21]

4.2. Parallel trends assumption

An important limitation of a DiDiD analysis is the assumption that the outcomes in the treatment and control groups would have followed parallel trends in the absence of the pandemic. For this purpose, we have relied on coarsened exact matching. Coarsened exact matching (CEM) is a matching strategy developed by Iacus et al. (2012), which reduces the impact of confounding on observational causal inference. The strategy consists of simultaneously matching using a set of confounders which are "coarsened", reducing the number of possible matching values for a given covariate with the aim of increasing the number of matches achieved.[22]

After applying the CEM method, a weighting variable is estimated to equalise the number of observations within the comparison groups, which takes values between 0 and 1. To check the balance of two comparison groups, we draw on a multivariate imbalance measure the size of which depends on the dataset and the selected covariates, and takes values ranging between 0 (perfect overall balance) and 1 (maximum imbalance), e.g., a larger value refers to a larger imbalance between two groups(Green et al., 2015).[23]

In our study, CEM has been used to make the two groups of respondents to the Eurobarometer surveys (80.2 and 93.1) statistically equivalent, based on a number of covariates including age, gender, age when finishing education, household size, economic activity and size of municipality.[24] The final sample after CEM contains 51,861 observations (25.874 from EB80.2 and 25,987 from EB93.1), which represents 93.66% of the initial sample.

An additional advantage of the CEM estimator over the standard matching procedure is that it allows us to control for unobserved time invariant factors. This implies that we assume that the outcome variables of interest of the treated and control units, in the absence of any treatment exhibit the same growth trajectory, e.g., the parallel trend assumption of the DiD method.

4.3. Canonical estimation

The canonical DiDiD model presumes the existence of two groups, the treated and the control group, and two time periods. When the common trend assumption is satisfied, the two-way fixed effects estimator is a linear combination of treatment effects across treated units. However, such estimates can be biased when treatment effects change over time within treated units (Goodman-Bacon 2021). Treatment effect heterogeneity in such a circumstance require a series of alternative estimators (Callaway and Sant'Anna 2020, Sun and Abraham, 2020). However, these estimators may have less statistical power than the pooled estimator, and Marcus and Sant'Anna (2021) find that when facing a limited number of groups and time periods (as in our case), it may be reasonable to adopt a "weaker" version of the parallel trend

[21] In additional specifications, we also show that our results are robust to using the Donald and Lang (2007) method to calculate standard errors.

[22] CEM works as follows. First, it makes a copy of the set of covariates chosen for matching. Second, the variables are broken down into different meaningful strata (i.e., into equal intervals of the same size or into intervals of different dimension from each other), through user choice automatically or through the CEM algorithm. Third, a unique stratum is created for each observation and each observation is placed in a stratum. The strata created are reassigned to the original data set, and any strata that does not contain at least one treated and one control unit is removed. Thus, the treatment effect is based on the matching provided by the algorithm, since the difference between treated and control units is obtained from the difference in the outcome variable between units belonging to the same strata. Finally, the higher the coarsening (higher number of strata), the lower the imbalance, as well as the lower the number of matches provided by the CEM.

[23] See Table A2 for L1 statistics before and after CEM.

[24] Muennig et al., 2017 and Tetteh et al. (2019) have found that CEM is preferable to other matching procedures (e.g., propensity score matching) in terms of more efficient processing and reduced model dependence, variance and bias. Ripollone et al., (2020) also showed that optimal performance is warranted only when the vector of important confounders is relatively small (fewer than 10), which is fulfilled in our case.

Table 2
Heterogeneous estimates of health system trust (HST) – DiDiD estimates.

Dependent variable: HST	Citizenship		Difficulties making ends meet			Self-reported social class			Age stopped education			
	Immigrant	National	Always	Sometimes	Never	Working class	Middle class	Higher class	< =15years	16–18 years	19–22 years	> =23 years
Mean(Trust)	2.8819	3.1377	2.5024	2.7225	3.0190	2.7494	2.9496	3.0737	2.8664	2.8172	2.8878	2.9758
Std.Dev.(Trust)	(0.870)	(0.842)	(0.9179	(0.853)	(0.844)	(0.866)	(0.865)	(0.896)	(0.885)	(0.867)	(0.875)	(0.863)
RM_t	-0.0079***	0.0244 * *	-0.0024	0.0019	-0.0283***	-0.0103 * **	-0.0057	0.0027	-0.0352***	-0.0046	-0.0093 * *	-0.0067 * *
	(0.0017)	(0.0108)	(0.0018)	(0.0033)	(0.0020)	(0.0028)	(0.0021)	(0.0134)	(0.0050)	(0.0031)	(0.0035)	(0.0030)
	-0.00004	**-0.00020**	**-0.00003**	**0.00000**	**-0.00010**	**-0.00005**	**-0.00003**	**0.00003**	**-0.00020**	**-0.00003**	**-0.00003**	**-0.00005**
$Year_{2020}$	0.3668 * *	6.8655 * **	0.8396	0.8106 * **	-1.0844***	-0.1127	0.6757	39.0808	-1.9776 ***	0.5852 *	0.3394	0.4856
	(0.1819)	(−1.7936)	(0.5452)	(0.3442)	(0.2194)	(0.2996)	(0.2304)	(12.6685)	(0.5277)	(0.3260)	(0.3743)	(0.3216)
	12.8812	**135.1306**	**31.6832**	**28.7548**	**-32.3819**	**-4.1911**	**22.9057**	**426.7587**	**-66.7624**	**20.8667**	**11.9055**	**16.4271**
$RM_t Year_{2020}$	-0.0027	-0.0600***	-0.0085***	-0.0076 * *	0.0116 * **	-0.0014	0.0061	-0.0125	-0.0199 ***	0.0061 *	0.0022	0.0035
	(0.0018)	(0.0117)	(0.0033)	(0.0034)	(0.0022)	(0.0030)	(0.0024)	(0.0137)	(0.0053)	(0.0033)	(0.0037)	(0.0032)
	0.0000	**-0.0005**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**-0.0002**	**0.0001**	**0.0000**	**0.0000**	**0.0000**
Age 31–45·RM_t·$Year_{2020}$	-0.0163	0.1448	-0.3089 * *	0.0219	0.0415	-0.0305 * **	0.2270	0.1948 * **	-0.3127	0.1246 *	-0.1251	-0.0625
	(0.0441)	(0.4235)	(0.1457)	(0.0799)	(0.0635)	(0.0085)	(0.0708)	(0.0528)	(0.2557)	(0.0776)	(0.0833)	(0.0842)
	-0.0007	**0.0531**	**-0.0358**	**0.0017**	**0.0027**	**-0.0021**	**0.0139**	**0.0595**	**-0.0675**	**0.0089**	**-0.0095**	**-0.0050**
Age 46–64·RM_t·$Year_{2020}$	0.1478 * **	0.9083 * *	-0.0887 * *	0.1537 * *	0.0152 * *	-0.0562 * **	0.0607 * **	0.1798 * **	-1.0281 ***	0.3772 * **	0.1867 *	0.0420 * *
	(0.0483)	(0.6131)	(0.0444)	(0.0817)	(0.0071)	(0.0188)	(0.0234)	(0.0838)	(0.3262)	(0.0869)	(0.1073)	(0.0186)
	0.0051	**0.4106**	**-0.0095**	**0.0100**	**0.0008**	**-0.0034**	**0.0033**	**0.0564**	**-0.1435**	0.0190 * **	0.0120 * *	0.0036 * *
Age 65 +·RM_t·$Year_{2020}$	0.1288 * **	2.8525 * **	-0.1170***	0.0333 * *	0.0070 * **	-0.0092	-0.0278	0.4872	-0.2421 ***	**0.4563**	**0.0735**	**0.1308**
	(0.0438)	(0.6334)	(0.0408)	(0.0167)	(0.0307)	(0.0765)	(0.0550)	(0.5911)	(0.0950)	(0.0778)	(0.0276)	(0.0483)
	0.0059	**5.0801**	**0.0188**	**0.0034**	**0.0004**	**-0.0008**	**-0.0017**	**0.4520**	**-0.0241**	**0.0369** ***	**0.0074** * **	**0.0149** ***
Intercept	3.4110 * **	12.991 * **	2.7041 * **	2.4585 * **	5.0325 * **	3.5159 * **	3.2912 * **	2.5137 * *	5.2899 * **	3.0952	3.5204	3.3658
	(0.1676)	(1.0059	(0.4809)	(0.3156)	(0.2008)	(0.2692)	(0.2113)	(1.5027)	(0.4829)	(0.2930)	(0.3418)	(0.2911)
N	51,861	51,861	51,861	51,861	51,861	51,861	51,861	51,861	51,861	51,861	51,861	51,861
R^2	0.2237	0.2885	0.2138	0.2094	0.2318	0.2193	0.2283	0.2528	0.2327	0.2259	0.2301	0.2285
F	726.512	42.139	40.828	47.693	661.473	184.179	531.103	108.219	148.016	253.670	243.533	242.098

Note: This table reports the effects of triple difference (DiDiD) estimates of relative mortality across age cohorts on HST. The coefficient in bold under the standard error in brackets report effect of one standard deviation increase of regressor on HSTmeasured both as a continuous variable or as a percentage increase of average trust for binary regressors). Relative mortality in 2020 is a continuous variable in all regressions (using model M6 of Table 1). All regressions have been estimated using the final sample after applying CEM. Covariates include age cohort include sex, nationality, region of residence, marital status, age when finishing education, economic activity, household characteristics (size and number of people younger than 10, between 10 and 15, aged 15 and older), difficulties for making ends meet, having internet and self-reported social class. Robust standard errors clustered at NUTS-2 level. Standard deviations in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3
OLS and IV estimations of the HST effect on the perceived ease of compliance with lockdown restrictions.

Dependent variable: COMPLY	Relative Mortality (RM_{2020}) as a binary variable							
	OLS				IV			
	M1	M2	M3	M4	M1	M2	M3	M4
HST	0.2198 * **	0.2195 * **	0.2179 * **	0.2117 * **	0.4555 * **	0.3643 * **	0.3601 * **	0.2964 * **
	(0.0120)	(0.0123)	(0.0122)	(0.0120)	(0.0153)	(0.0162)	(0.0162)	(0.0165)
	0.0025	0.0025	0.0025	0.0024	0.0065	0.0055	0.0055	0.0046
RM_{2020}	0.3849 * **	0.4218 * **	0.4161 * **	0.2066 * **	0.1774 * **	0.1704 * **	0.1718 * **	0.1648 * **
	(0.0210)	(0.0442)	(0.0491)	(0.0533)	(0.0135)	(0.0138)	(0.0138)	(0.0137)
	12.204	**13.375**	**13.194**	**6.551**	**5.625**	**5.403**	**5.447**	**5.226**
Case rate	0.1266 * **	0.1301 * **	0.1251 * **	0.0954 * **	0.0002	0.0003	0.0003	0.0005 *
	(0.0035)	(0.0058)	(0.0064)	(0.0077)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
	0.0004	0.0007	0.0008	0.0007	0.00001	0.00001	0.00001	0.00001
N	27,997	27,997	27,997	27,997	27,997	27,997	27,997	27,997
R^2	0.1714	0.1746	0.1755	0.1807	0.0213	0.0562	0.0583	0.0809
F/chi2	340.412	436.733	361.383	359.986	12,345.994	15,797.916	16,347.532	21,914.695
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Relative Mortality (RM_{2020}) as a continuous variable							
	OLS				IV			
	M1	M2	M3	M4	M1	M2	M3	M4
HST	0.2198 * **	0.2195 * **	0.2179 * **	0.2117 * **	0.4730 * **	0.3803 * **	0.3764 * **	0.3093 * **
	(0.0120)	(0.0123)	(0.0122)	(0.0120)	(0.0154)	(0.0163)	(0.0163)	(0.0166)
	0.0025	0.0025	0.0025	0.0024	0.0068	0.0058	0.0058	0.0048
RM_{2020}	0.3849 * **	0.4218 * **	0.4161 * **	0.2066 * **	0.0774 * **	0.0704 * **	0.0718 * **	0.0480 * **
	(0.0210)	(0.0442)	(0.0491)	(0.0533)	(0.0135)	(0.0138)	(0.0138)	(0.0137)
	0.0076	**0.0175**	**0.0192**	**0.0103**	**0.0010**	**0.0009**	**0.0009**	**0.0006**
Case rate	0.0765 * **	0.0809 * **	0.0800 * **	0.0702 * **	0.0006	0.0006 * *	0.0006 * *	0.0008 * **
	(0.0010)	(0.0018)	(0.0020)	(0.0023)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	0.0001	**0.0001**	**0.0002**	**0.0002**	**0.00001**	**0.00001**	**0.00001**	**0.00001**
N	27,997	27,997	27,997	27,997	27,997	27,997	27,997	27,997
R^2	0.1714	0.1746	0.1755	0.1807	0.0168	0.0536	0.0557	0.0798
F/chi2	340.336	444.075	366.365	363.049	12,521.952	15,980.474	16,561.554	22,089.808
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: Estimates in bold under the estimates in brackets report the effect of one standard deviation increase of the regressor on the dependent variable (for continuous variables) or the percentage variation with respect to the mean (for binary variables). The upper part of the table report OLS and IV regressions using "Relative Mortality in 2020 with respect to average 2016–2019" as a binary variable (1 if relative mortality is above zero and 0 otherwise). The lower part of the table reports OLS and IV regressions using "Relative Mortality in 2020 with respect to average 2016–2019" as a continuous variable. Model M1 includes as explanatory variables: age cohort, sex, nationality and region of residence. Model M2 includes the same explanatory variables as M1 and additionally marital status and age when finishing education. Model M3 includes the same explanatory variables than M2 and economic activity. Model M4 includes the same explanatory variables than M3 and also household characteristics (size and number of people younger than 10, between 10 and 15, aged 15 and older), difficulties for making ends meet, having internet and self-reported social class. Robust standard errors clustered at NUTS-2 level. IV regressions use four instruments (high risk countries, moderate risk countries, low risk countries and very low risk countries according to the Inform COVID-19 Risk Index) to instrument the potential endogenous variables (trust in healthcare, relative mortality in 2020 and average case rate). Standard deviations in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

assumption.[25]

The DiDiD is an intention-to-treat analysis in which the coefficient α_7 depicts the effect of the relative mortality on trust among respondents in regions with higher RM. To interpret the DiDiD effect as the causal effect of COVID-19, the incidence of the pandemic must be uncorrelated with other time-varying determinants of trust in healthcare in our sample. This assumption would be violated if the pandemic induced selection into our sample (for example, if the level of HST between those who died between the two waves of the Eurobarometer was not randomly distributed, which would in turn affect the sample of respondents in 2020).

To evaluate the plausibility of these concerns, we report the results from regressions that estimate the DiDiD model using observable respondent characteristics as dependent variables (and thus omitting the controls X_{irct}). As we do not include individual-level controls in these regressions, we collapse the data to respondent's age-region/year level. Results in Tables A4-A6 suggest that the pandemic is fundamentally uncorrelated with the explanatory variables Therefore, it seems unlikely that differential demographic trends drive our estimates (reported in Section 5.1).

4.4. *Effect of trust in healthcare on the perceived ease of compliance with lockdown restrictions*

Previous research indicates that public trust in the government is an important determinant of an individual's adherence to regulations (Chanley et al., 2000),[26] insofar as it legitimises government's decisions (Marien and Hooghe, 2011), especially when individual freedoms are restricted (e.g., in a lockdown). Consistently, we examine whether HST impacts on the perceived ease of compliance with pandemic regulations as follows:

[25] As the weights are proportional to the residuals from a regression of treatment on country, region and year effects, we have checked that the residuals from a regression of the outcome variable on region and year fixed effects are linearly related to the residuals from a regression of treatment on region and year fixed effects and the slope of this linear relationship does not differ between the treatment group and the comparison group (results available upon request).

[26] For example, in relation to the SARS outbreak in Singapore, high trust in government made it easier for most Singaporeans to comply with control measures (Deurenberg-Yap et al., 2005). In contrast, during the Ebola outbreak in West Africa, distrust in institutions was found to significantly decrease the likelihood of ease of compliance with control recommendations (Blair et al., 2017).

$$COMPLY_{irc} = \beta_0 + \beta_1 HST_{irc} + \beta_2 RM_{rct} + \beta_3 Casesf_{rc} + \kappa' X_{irc} + \lambda_r + \mu_c + \varsigma_{irct} \quad (6)$$

where $COMPLY_{irct}$ measures the ease of compliance with lockdown restriction of individual *i* living in region *r* of country *c* (using the Likert scale that ranges from from 4 which corresponds to "*very easy to cope with*", to 1 which denotes "*very difficult to cope with*"). HST_{irc}, RM_{rct} and X_{irc} are defined as in the previous model. As in the DiDiD model, RM enters the regression either as a binary variable or as a continuous variable. $Casesf_{rc}$ denote the average of 14-day case rate of newly reported COVID-19 cases per 100,000 inhabitants for region *r* of country *c* (since the onset of the pandemic until the day of the interview).

Further, we examine the so-called "*Cummings effect*" to add additional credibility to the causal effect of our estimates. This effect is named after Dominic Cummings, senior aide to the British Prime Minister, who was caught not complying with lockdown regulations, traveling with his wife (a COVID-19 suspect) and his son. Numerous scientists expressed their concern that such actions could undermine confidence in the health authorities.[27] Similar regulation breaches have been detected in Greece,[28] New Zealand,[29] Norway,[30] Spain,[31] which can undermine trust and individuals' behaviours, contributing to further outbreaks,[32] and lead to a relaxation of an individual's adherence to health recommendations, which may give rise to further outbreaks (Wong and Jensen, 2020).

As for the effect of RM and number of reported cases, we hypothesise that it may increase risk perception (Bundorf et al., 2021), thereby increasing the preferences for staying at home (Eder et al., 2021) and making it easier to comply to regulations (Lunn et al., 2020). However, if mortality was large enought, we hypothetise that it could be perceived as a signal of health system failure. Hence, whether RM affects HST is an empirical question. Given that a very strict lockdown may increase the likelihood of breaking the rules, there is protential endogeneity to take into consideration. That is, the potential endogeneity of the variables relative mortality (RM_{rc}) and average case rate ($Cases_{rc}$) should be specifically considered as follows:

$$RM_{rc} = \gamma_0 + \gamma_1' Z + \gamma_2' X_{irc} + \tau_r + \upsilon_c + \varrho_{irct} \quad (7)$$

$$Cases_{rc} = \delta_0 + \delta_1' Z + \delta' X_{irc} + \psi_r + \iota_c + \varphi_{irct} \quad (8)$$

In Eqs. (7) and (8), the vector *Z* refers to exogenous variables. In this paper, we use as instrumental variables approach that uses as an instrument the classification of the 28 countries into quartiles according to the INFORM Covid Risk Index,[33] which relies on three dimensions: "Hazard and Exposure", "Vulnerability" and "Lack of Coping Capacity" which focus on structural factors.[34] Using the value of the index, we classify the values into quartiles (very low risk, low risk, moderate risk and high risk) as reported on Table C1 (see Appendix C for more information of the items included in each dimension).[35] Table C2 displays the average values of HST by RM and the number of confirmed cases in 2020.

5. Results

5.1. Trust in healthcare system

Table 1 displays the results of the model estimation for HST. The first three specifications M1-M3 use RM defined as a binary variable (1 if excess mortality exceeds zero, namely, if mortality in the respective wave was higher than the 2016–2019 average, 0 otherwise). The subsequent three specifications M4-M6 draw on RM defined as a continuous variable. Models M1 and M4 report the estimates of a DiD model that compares the changes in trust before and after the pandemic between the 31–45, 46–64 and 65 + cohorts (treatment group) compared to the youngest cohort (control group). M2 and M4 report the estimates of a DiD specification that compares the changes in trust before and after the pandemic in regions with over-mortality relative to the 2016–2019 average (treatment group) and with RM below the 2016–2019 average (control group). Finally, models M3 and M6 estimate the DiDiD model of Eq. (5). Furthermore, estimates for continuous varables are interpreted as the effect of a one standard deviation increase of the covariate on HST, and for binary variables as the average percentual point change in HST.

Our descriptive analysis reveals an increase in HST in the year 2020 (compared to 2013) ranging between 2.67% in M1 and 6.24% in M3. However, living in a region with excess mortality leads to an additional reduction of HST (−0.29% in M1; −0.27% in M3). *One standard deviation increases in RM decreases HST* between *0.0005* (M4) and 0.0025 points (M6). Our estimates suggest evidence of an accentuated negative effect of RM in 2020.

Nonetheless, the effects vary by age cohorts, and more specifically, we find that people aged 46–64 and 65 + reveal a higher HST (6.59% and 10.17% in M3, respectively). HST significantly increased in 2020 compared to 2013 (2.96% for 46–64% and 6.14% for 65 + in M1). As

[27] Fancourt et al. (2020) analysed 220,755 interviews conducted with 40,597 individuals between April 24 and June 11, 2020, in England, Scotland and Wales, and reported a reduction in confidence in government in England, starting on May 22nd, although no comparable behaviour was found for confidence in the governments of the devolved nations. A knock-on effect of such actions was a decrease in public adherence to the guidelines of the health authorities (Marien and Hooghe, 2011). Fancourt et al. (2020) shows that before the Cummings breach became known (on May 22) there had been a relaxation in compliance, but the gap between England and Wales and Scotland widened in the weeks that followed.

[28] Greek PM accused of breaking coronavirus lockdown rules — again – POLITICO

[29] Coronavirus: NZ health minister breaks lockdown at beach - BBC News

[30] Norway's prime minister investigated for breaking lockdown rules | Financial Times (ft.com)

[31] Fernando Simón, sábado de surf en Portugal en plena oleada de rebrotes (abc.es)

[32] Vinck et al. (2019) explored the role of mistrust and misbeliefs on preventive behaviours during an Ebola outbreak in the Republic of Congo. They reported a lower likelihood of seeking healthcare in case of presenting symptoms and adopting preventive behaviours.

[33] The INFORM COVID-19 Risk Index is an adaptation of the Inform Epidemic Risk Index that tries to identify: "*countries at risk from health and humanitarian impacts of COVID-19 that could overwhelm current national response capacity, and therefore lead to a need for additional international assistance*" (Poljanšek et al., 2020).

[34] Each of the 3 dimensions is measured on a scale between 0 and 10 in which a higher value indicates that the country faces more adverse conditions. The aggregation of the indicators has been performed following the INFORM model (De Groeve et al., 2014).

[35] The use of the INFORM Covid-19 Risk Index might raise some doubts about its suitability, if one suspects that countries with higher values of this index, and therefore less preparedness to face a health emergency, would have opted to impose more restrictive mobility measures. However, this hypothesis does not seem at all plausible for three reasons. First, the INFORM Covid-19 Risk Index was published on April 20th, 2020, e.g., when the first wave of the pandemic had already begun. Second, Table C3 shows the chronology of mobility and containment restrictions approved in all the countries analysed, and all countries had enacted severe containment measures before the date of publication of this index. Third, Figure C1 shows the relationship between the INFORM Covid-19 Risk Index and the average Oxford Covid-19 Stringency Index during the first wave of the pandemic, showing that there is no positive relationship between the two variables.

expected, the effect is lower when a region exhibits excess mortality among individuals aged 45–64 and over 65 + (−0.20% according to M3) age cohort years of ages. Such a negative effect is offset by the coefficient of the triple interaction of age, year and region over mortality, which is positive for both age cohorts, although the overall effects turn out to be negative for the cohort aged 31–45 years (−0.20%).

When we turn to examining the effect of RM as a continuous variable, Fig. 1 displays the predicted HST by age cohort. For all ages, HST is higher in 2020 than 2013, unless excess mortality exceeds the average of 2016–2019. *Indeed, HST increases with RM* unless *excess mortality exceeds the threshold of 20% relative for the period 2016–2019, where we observe a change in trend for all age cohorts.*

5.2. Heterogeneity

Table 2 reports the heterogeneous effects of several relevant covariates extending the specification M6 reported in Table 1. Estimates suggest that in 2020, a higher relative exposure to RM gave rise to a sharp increase in HST among nationals over 45 years of age (46–64 and 65 +). Similarly, we find a comparable effect when we evaluate the effect among migrants, but the effect is significantly lower. Next, we examine the heterogeneity by individuals self-reported difficulty in making ends meet, and we document, as expected, a negative effect among lower socio-economic status individuals, which is higher among the cohort aged 65 + years. The effect amongst those who always have difficulties in making ends meet exceeds by more than 10 times that of those who have no difficulties at all. Thus, these results suggest that in 2020 and in the face of excess mortality, lower income households have been more prone to distrust the health system, and such gap increases with age.[36] Finally, we document significant heterogeneity by educational attainment. Consistently, we observe a stronger reduction in HST among all age cohorts that left school before the age of 16.

5.3. Perceived ease of compliance with COVID-19 restrictions

Next, we examine how individual variation in HST affects people's perceived ease of compliance with lockdown restrictions drawing on an instrumental variable strategy.[37]

Table 3 displays the OLS and IV estimation results for the degree of ease in complying with lockdown constraints. IV coefficient are estimated using a three stage least squares (3SLS) specification, which provides more efficient estimates (Greene, 2008). The upper panel of the table displays the estimates considering RMas a binary variable, and the lower panel displays the estimates considering that RM is a continuous variable.

We expect OLS estimates to underestimate the effect of HST but overestimate the effect of RM and case rates compared to IV estimates.[38] Table 4 suggests that *one standard deviation increase in HST increases the probability in complying with the restrictions, and the effect ranges between 0.0046 and 0.0065 points (IV).*

Similarly, when we focus on OLS estimates, we find that a one standard deviation increase in HST gives rise to an increase in ease of compliance with COVID-19 regulations of 0.0007 points, but such effect becomes negligible in the IV estimation. Living in a region with excess mortality (binary variable) increases ease of compliance with mobility constraints by 5.22% compared to the mean value (that is, one percentage point smaller compared to M4 in the OLS estimation). Similarly, when we consider the continuous dimension of this variable, estimates suggest that a one standard deviation increase in RM increases the perceived ease of compliance with the pandemic regulations by 0.0006 points (compared to 0.0103 in the OLS estimation).

Fig. 2 displays the predicted level of ease of compliance with pandemic regulations as a function of age cohort, HST and mortality in 2020 relative to the 2016–2019 average. Consistently with estimates suggesting lower levels of HST among such age group, we show that younger cohorts (18–30, 31–45 years) reveal a reduction in the perceived ease of compliance (or an increase in lockdown compliance difficulties: −0.08 or −0.07 points, or a decrease by 2.2%−2.6% with respect to the mean) for mortality levels above 10% compared to the 2016–2019 average.

Finally, its worth noting that we find a nonlinear effect in older cohorts (46–64, 65 + years), namely an initial decline (easier compliance with lockdown), but only up to a RM of 105. From this point on, the ease of compliance rises to a RM of 120. That is, when COVID-19 mortality exceeds 120, we find a decrease in the perceived ease (or increase in the difficulty) of compliance with restrictions irrespectively of the age of the respondent. Although we hypothesised that the high mortality rate could be interpreted as an increased risk of contagion and, as a result, a greater preference to seek safety at home, our estimates suggest the opposite effect, probably indicating that higher level of relative COVID-19 are a signal of health system failure to control the pandemic.

5.4. Heterogeneity for ease of compliance perceptions

Table 4 shows the results of the IV estimates of the effect of HST on ease of compliance by age, nationality, age at leaving school and two measure of socio-economic status, namely difficulties in making ends meet and self-reported social class.

We find that the effect of HST on the perceived costs of compliance with pandemic regulations increases with restrictions, and [39]is 45% higher among older cohorts and. with years of education.[40] Indeed, the effect of HST is 105% higher among those highly educated (compared to the lowest educated).[41] That said, more educated people may have

[36] These estimates are consistent with estimates of the self-reported social class: in the cohort aged 31–45 years, we document a different effect among those regarding themselves as "working class", an effect nearly 30 times higher than that of those who consider themselves to be "higher class".

[37] First, we verify that the referred instruments satisfy two conditions: (1) relevance or being sufficiently correlated with the suspected endogenous variable, and (2) exogeneity or being distributed independently of the error process. The results presented in Table C4 strongly reject the null hypothesis of underidentification. To detect weak instruments, there are several informal procedures, such as the first-stage partial R^2, which measures the contribution of the excluded instruments to explain variation in the endogenous variable, and the first-stage partial F-statistics on the excluded instruments. All the F-statistics are above 10 and the partial R^2 suggesting that our instruments are relevant and strong. Since the Cragg-Donald-based test for weak instruments assumes homoscedastic errors, we also present the Kleibergen-Paap Wald rk F-statistic, which is valid in case of non-i.d. errors (Kleibergen and Paap, 2006). We find that the Cragg-Donald and Kleibergen-Paap Wald rk F statistics reject the weakness of the instruments. As the number of instruments is larger than the number of potential endogenous variables, we test for over-identification using the Hansen-Sargan (Hansen, 1982). The null hypothesis is that the instruments are valid (e.g., uncorrelated with the error term) and that the excluded instruments are correctly excluded from the estimated equation. The test statistics show that exogeneity is rejected at the 5% significance level. All three instrument options have been validated.

[38] While OLS estimates suggest that individuals are more likely to perceive lower costs to comply with lockdown restrictions if they live in high contagion or high mortality region after the pandemic, IV estimates reveal that this is not the case.

[39] One standard deviation increase in HST increases ease of compliance by 0.0086 points for the 18–30 and 31–45 age cohorts, 0.0107 points for 46–64 years and 0.125 points for 65+.

[40] So that one standard deviation increase in trust increases ease of compliance by 0.0078 points if studying up to 15 years or less, 0.0114 points (16–18 years), 0.0121 points (19–22 years) and 0.0160 points (23 years or older).

[41] Most studies that have addressed the relationship between trust and education have focused on trust in political powers. Some studies (Hetherington, 1998; Anderson and Singer, 2008) document a positive relationship between trust and education.

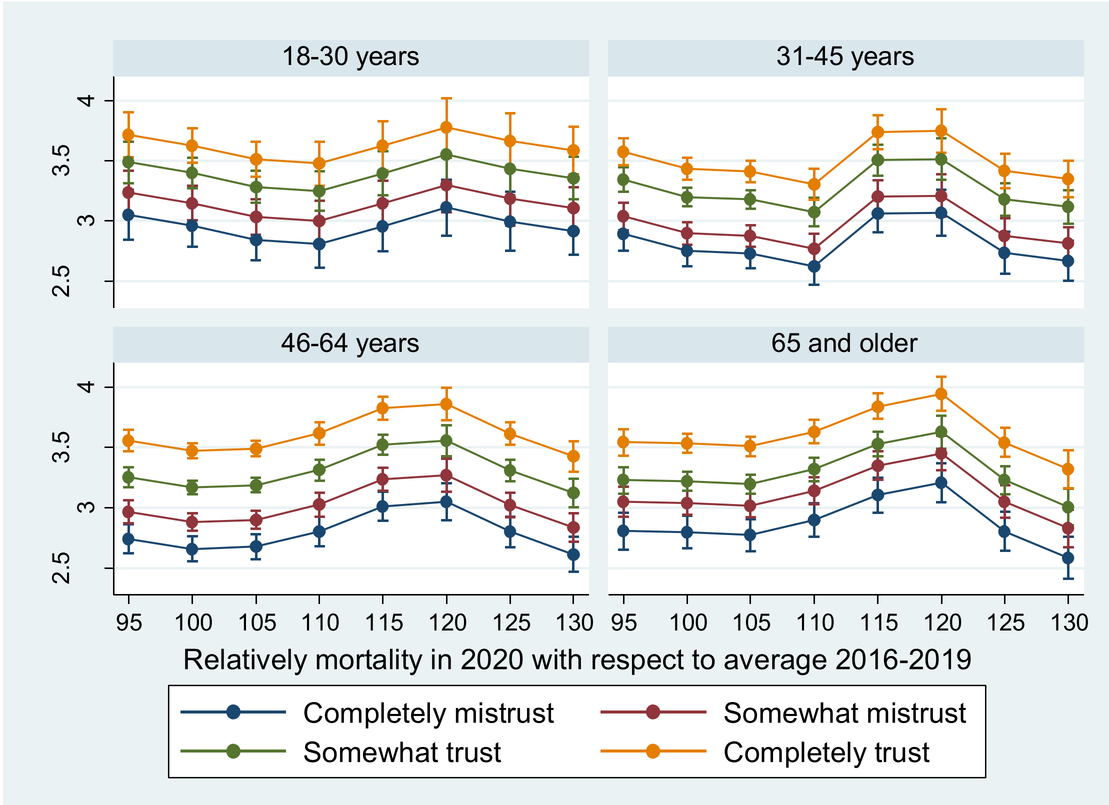

Fig. 2. Predicted ease of compliance with lockdown restrictions after estimation of IV model for the variables 'trust level in healthcare system' and 'relative mortality (RM)' with interactions by age. Estimations have been performed using the final sample after CEM. Note: Predicted probabilities obtained after estimating an IV regression with the following explanatory variables: sex, nationality and region of residence, marital status, age when finishing education, relation with economic activity, household characteristics (size and number of people younger than 10, between 10 and 15, aged 15 and older), difficulties for making ends meet, having internet and self-reported social class. Endogenous variables (relative mortality in 2020 with respect to average 2016–2019 (continuous variable), trust in healthcare system and their interaction with age. Instruments used: classification of countries by Inform COVID-19 Risk Index. Robust standard errors clustered at NUTS-2 level.

higher expectations about the performance of political institutions (Cook and Gronke, 2005) and might be less tolerant with corruption (Hakhverdian and Mayne, 2012).[42]

Next, we turn to examine the effects by nationality, and we find that nationals exhibit a 10% higher perceived ease of compliance than migrants, though HST reduces such gap[43] As expected, we find that the effect of trust on the ease of compliance is greater for households that do not face financial constraints,[44] and consistently, the average degree of ease of compliance with restrictions is almost 16% among those who consider themselves belonging to higher class compared to working class. This result is consistent with Newton et al. (2017) and Rieger and Wang (2022) who document higher levels of trust among the population among socioeconomic status individuals, as lower-income people are more likely to work in jobs not suitable for home working (Adam-Prassl et al., 2020), are more likely to experience financial stress (Berchick et al., 2019).

5.5. Mechanisms

Finally, we propose two mechanisms to help explain our effect, namely the compulsory nature of the restrictions,[45] which might not be seen as justified, and the effect of the restrictions on the economy.

We rely on two questions from Eurobarometer 93.1. The first question refers to whether the restrictions impact on the country's economy.[46] We define three binary variables that depict the balance between health and economic objectives underpininng *COVID-19 restrictions*. Three possible responses are identified: 41% of respondents report that there was a balance in their country between health and economic protection, while 35% report that pandemic responses in their country were too focused on health goals at the expense of the economy (see Table A3). Table A7 displays the results of the OLS regressions for each of the three binary variables defined above. For each dependent variable, eight different specifications have been estimated, four using RM_t as a binary variable and another four using RM_t as a continuous variable. We find that one standard deviation increase in HST decreases the probability of reporting that measures weight too heavily-on health by

[42] Hence, education is a proxy variable for both cognitive skills and information processing ability and is found to reinforce the effect of trust in the healthcare system on ease of compliance to a greater extent than biological age.

[43] The survey does not provide information on the health coverage of respondents, but it could be that unequal access to healthcare between nationals and immigrants is the cause of the effect among immigrants.

[44] One standard deviation increase in trust in the healthcare system increases the ease of compliance with restrictions by 0.0107 points if there are no difficulties in making ends meet, compared to 0.058 points for households that always struggle to make ends meet (i.e., almost twice).

[45] Indeed, Schmelz (2021) contends that when these measures are voluntary rather than mandatory, people are more willing to comply. Other evidence documents that higher confidence in public institutions increases compliance with health regulations (Adamecz-Völgyi and Szabó-Morvai, 2021).

[46] "*Thinking about the measures taken by the public authorities in your country to fight the Coronavirus and its effects, would you say that: (1) these measures focus too much on health to the detriment of the economy; (2) these measures focus too much on economy to the detriment of health; (3) a balance has been reached?*".

Table 4
Heterogeneous IV estimates of the HST effect on perceived ease of compliance with lockdown restrictions.

Dependent variable: COMPLY	**Age 18–30**	**Age 31–45**	**Age 46–64**	**Age 65 +**	**National**	**Immigrant**	**Stopped educ < =15years**	**Stopped educ 16–18 years**
Mean (Comply)	3.1035	3.1035	3.1666	3.2434	3.1627	2.8790	2.9373	3.0470
Std.dev. (Comply)	1.0493	1.0493	1.0640	1.0617	1.0602	1.1687	1.1137	1.0661
HST	0.3249 * **	0.3431 * **	0.5066 * **	0.5174 * **	0.5002 * **	-0.0195 * *	0.2361 * **	0.4326 * **
	(0.0278)	(0.0308)	(0.0224)	(0.0257)	(0.0152)	(0.0090)	(0.0370)	(0.0282)
	0.0086	**0.0086**	**0.0107**	**0.0125**	**0.0072**	**-0.0002**	**0.0078**	**0.0114**
RM_{2020}	0.0200	0.0222	0.0522 * **	0.0501 * **	0.0442 * **	-0.0061	-0.0182	0.0533 * **
	(0.0160)	(0.0157)	(0.011)1	(0.013)	(0.0075)	(0.0101)	(0.0171)	(0.0130)
	0.0003	**0.0003**	**0.0005**	**0.0006**	**0.0003**	**-0.0001**	**-0.0003**	**0.0006**
Case rate	0.0011	0.0001	0.0053 * **	0.0542 * **	0.0000	0.0014 *	0.0014 *	0.0005
	(0.0007)	(0.0006)	(0.0004)	(0.0004)	(0.0003)	(0.0008)	(0.0008)	(0.0006)
	0.00001	**0.00001**	**0.00001**	**0.00001**	**0.00001**	**0.00001**	**0.00001**	**0.00001**
N	3897	6283	9653	7514	27,090	907	1131	10,664
R^2	0.0312	0.0379	0.0204	0.0243	0.0094	0.0090	0.0250	0.0219
chi2	1445.718	1620.450	5594.064	4538.750	11,841.831	267.849	561.802	2526.799
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Finished Education before 22 years	**Finished Education after 23 years**	**Difficulties making ends meet: Never**	**Difficulties making ends meet: Sometimes**	**Difficulties making ends meet: Always**	**Working class**	**Middle class**	**Higher class**
Mean (Comply)	3.2055	3.3008	3.3258	2.8717	2.6136	2.9789	3.1763	3.4544
Std.dev. (Comply)	1.0397	1.0399	1.0039	1.0682	1.1624	1.1042	1.0461	1.0038
HST	0.4880 * **	0.6104 * **	0.4858 * **	0.3034 * **	0.3322 * **	0.2038 * **	0.4434 * **	0.3925 * **
	(0.0261)	(0.0272)	(0.0255)	(0.0316)	(0.0175)	(0.0310)	(0.0178)	(0.0259)
	0.0121	**0.0160**	**0.0107**	**0.0090**	**0.0058**	**0.0057**	**0.0075**	**0.0101**
RM_{2020}	0.0442 * **	0.0560 * **	0.0851 * **	-0.0190	0.0422 * **	0.0382 * **	0.0432 * **	0.0851 * **
	(0.0131)	(0.0122)	(0.0232)	(0.0132)	(0.0080)	(0.0131)	(0.0091)	(0.0211)
	0.0006	**0.0006**	**0.0017**	**-0.0002**	**0.0003**	**0.0004**	**0.0004**	**0.0018**
Case rate	0.0001	0.0007 *	0.0023 * *	0.0013 *	0.0004	0.0019 * **	0.0002	0.0017 * **
	(0.0005)	(0.0004)	(0.0011)	(0.0007)	(0.0003)	(0.0006)	(0.0003)	(0.0007)
	0.00001	**0.00001**	**0.00001**	**0.00001**	**0.00001**	**0.00001**	**0.00001**	**0.00001**
N	8713	4880	6770	6548	2097	2621	18,316	6770
R^2	0.0334	0.0176	0.0317	0.0303	0.0256	0.0237	0.0225	0.0212
F/chi2	2920.171	14,511.475	2312.434	1158.804	4764.929	2035.889	6755.778	3183.789
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note. Bold figures correspond to the effect of one standard deviation increase of the regressor over the dependent variable. Estimates refer to IV estimates for ease of compliance with lockdown restrictions using four instruments (high risk countries, moderate risk countries, low risk countries and very low risk countries according to the Inform COVID-19 Risk Index) to instrument the potential endogenous variables (trust in healthcare, relative mortality in 2020 and average case rate). In all regressions, RM_{2020} is a continuous variable. Covariates include age cohort include sex, nationality, region of residence, marital status, age when finished education, relation with economic activity, household characteristics (size and number of people younger than 10, between 10 and 15, aged 15 and older), difficulties for making ends meet, having internet and self-reported social class. Robust standard errors clustered at NUTS-2 level. Standard deviations in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

0.0012 pp, or too heavily-on economy by 0.0021 pp. In contrast, one standard deviation increase in HST, increases the probability of an individual to report that there was a good balance between health and economy by 0.0030 pp.

We find that an increase in RM in 2020 or an increase in relative case rate is consistently associated with a decrease in the perception that COVID-19 restrictions were overly weighting too much on health versus the economy. Living in a region with high excess mortality raises the perception that restrictions are overly weighting too much on the economy, and lowers the perception that restrictions are overly weighting too much on health.

The second question asks the extent to which the respondent regards policy restrictions to be justified: "*Thinking about the measures taken by the public authorities in your country to fight the Coronavirus and its effects, would you say that the limitations to public liberties were: (1) absolutely justified, (2), somewhat justified, (3) not very justified or (4) not at all justified?*". 44% reveal that restrictons were absolutely justified whilst 37% reveal they were quite justified (see Table A3).

Table A8 displays the results of the OLS regressions for each of the three binary variables defined above. For each dependent variable, eight different specifications have been estimated. We find that one standard deviation increase in HST increases the probability of reporting that lockdown measures are absolutely justified by 0.0026 pp. Importantly, living in a region with excess mortality increases (decreases) the justification of policy restrictions by 50%.[47]

6. Conclusion

This paper has examined whether changes in relative COVID-19 mortality (RM) exposure enhance or weaken healthcare system trust (HST), and whether HST influences how costly individuals perceived it was to comply with COVID-19 regulations. We document three sets of findings.

First, we find that on average that RM increased health system trust (HST), and that HST reduces the perceived costs to comply with COVID-19 restrictions. However, the effect is non-linear, as we show that

[47] In other words, one standard deviation increases in relative mortality in 2020 with respect to average 2016–2019 increases the probability that containment measures are absolutely justified by 0.002 pp. and decreases the probability of believing that measures are not at all justified by 0.004 pp.

exposure to 20% above average excess mortality reduces significantly HST, and the propensity to comply with regulations, offsetting the positive effect of trust in the healthcare system.

Second, HST increases with age and we find that the effect of RM on HST during the pandemic is heterogeneous across individuals age groups. That is, it increased HST among people 45–64 and 65 and over as they were mostly affected by the pandemic, but it decreases it among younger cohorts.

Third, we find that although HST leads to an increase in the perceived ease of compliance with COVID-19 restrictions, the effect was heterogeneous across age groups and varied between 0.0086 points (18–30 years) and 0.107 points (over 65 years) for each standard deviation increse in HST. That is, the effect of HST and perceived ease of compliance is 45% stronger for the older cohort, who are likely to perceive RM as a risk signal, whilst this might not be the case among younger individuals.

There are several explanations for these results including the presence of higher economic difficulties among younger individuals, as proxied by an effect of individuals reporting "difficulty in making ends meet" and "self-reported social status ". Consistently, we document that the effect of HST on the ease of compliance is weaker among households that face financial constraints. The negative effect of RM among younger people can be explained as blaming the health system for the spread of the pandemic, as well a the consequences it has had for their lives, jobs or businesses.

These results suggest that higher RM strengthens HST among individuals that are perceived to be more vulnerable. However, even such effect only holds so long as it does not exceed 20% of the average RM. This evidence suggests that the pandemic was especially challenging among younger age groups, for whom RM is not necessarily entailed higher risk exposure, and for whom higher RM is interpreted as a sign of failure that weaken their trust in the health system. Altogether, these estimates suggest that building HST can can reduce the perceived costs of compliance with regulations in a pandemic and explains the heterogeneous costs of compliance with regulations across age groups, which in turn might suggest that in the event of the pandemic, younger age individuals out to be compensated, if HST is expected to remain strong among such an age group.

Conflict of interest

No conflict of interest nor any funding for this project.

Data availability

Data is publicly available and the codes will be made available on request.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ehb.2023.101235.

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