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IZA DP No. 15462

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Corrado Giulietti
University of Southampton

Michael Vlassopoulos
University of Southampton and IZA

Yves Zenou
Monash University, IZA and CEPR

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

When Reality Bites: Local Deaths and Vaccine Take-up

We investigate whether COVID-19 deaths that occurred before vaccination rollouts impact subsequent vaccination take-up. We use data on local vaccination rates and COVID-19-related deaths from England measured at high geographic granularity. We find that vaccination take-up as of November 2021 is positively associated with pre-vaccine COVID-19-related deaths, controlling for demographic, economic, and health-related characteristics of the localities, while including geographic fixed effects. In addition, the share of ethnic minorities in a locality is negatively associated with vaccination rates, and localities with a larger share of ethnic minorities increase their vaccination rates if they are exposed to more COVID-related-deaths. Further evidence on vaccination intention at the individual level from a representative sample corroborates these patterns. Overall, our evidence suggests that social proximity to victims of the disease triggers a desire to take protective measures against it.

JEL Classification: H51, I12

Keywords: vaccination hesitancy, COVID-19, social interactions, information, behavior change

Corresponding author:
Michael Vlassopoulos
Department of Economics
University of Southampton
Southampton, SO17 1BJ
United Kingdom

E-mail: m.vlassopoulos@soton.ac.uk

"If I had the information I have today, we would have gotten vaccinated."

New York Times, July 30th 2021
(https://www.nytimes.com/2021/07/30/us/covid-vaccine-hesitancy-regret.html)

1 Introduction

In various situations, individuals make binary choices, in which the benefits and costs are not perfectly known, while being also influenced by social interactions. For instance, the decisions to engage in risky health behavior (Cawley & Ruhm, 2011, Hsieh & van Kippersluis, 2018), to commit crime (Becker, 1968, Damm & Dustmann, 2014), to adopt an agricultural technology (Bandiera & Rasul, 2006, Conley & Udry, 2010, Islam et al., 2018), to migrate (Borjas, 1999, Munshi, 2003), to participate in a retirement or other social program (Duflo & Saez, 2003, Dahl et al., 2014) are made without fully knowing the benefits or costs of these choices and are heavily affected by others' decisions. In these environments, a "local shock" that reveals information about the benefits or costs of the binary choice at hand may trigger agents to make a decision.

In this study, we focus on the decision to participate in the COVID-19 vaccination program. We examine whether a local shock, that is, the rate of COVID-19 deaths in one's local area, which reveals information about the disease severity, impacts vaccination take-up. Vaccination decisions against COVID-19 offer a uniquely suitable setting to study the extent to which people change their decisions related to a high-stakes issue when facing hard facts. First, these decisions have serious consequences for decision-makers, as they concern a new and highly infectious virus with a non-negligible risk of hospitalization or death and unknown long-term effects. Second, the World Health Organization has identified persistent vaccine hesitancy as a major public health issue.[1] It is well documented that, even in countries where the vaccine is widely available at no cost, there is imperfect take-up.[2] Vaccine hesitancy has been attributed to various factors, including low perceptions of health risks associated with the virus or concerns about side effects of the rapidly developed vaccine (Robertson et al., 2021, Razai et al., 2021, Allington et al., 2021). Often, these beliefs are fueled by misinformation around COVID-19 that circulates abundantly in the social media or through one's social networks and which undermines trust toward health authorities and science.

What information would convince COVID-19 skeptics to vaccinate? If the processing of the evidence is distorted by (mis)information that confirms one's beliefs while suppressing information that contradicts them (Epley & Gilovich, 2016), then it is unlikely that scientific facts will be very effective. By contrast, one might expect that skeptics or hesitants would be alarmed if they receive

[1] See https://www.who.int/news-room/spotlight/ten-threats-to-global-health-in-2019.
[2] See https://ourworldindata.org/covid-vaccinations.

news through their social networks that people close to them fall ill seriously or die from the disease. This type of hard evidence is more likely to lead skeptics to change their mind and vaccinate. A similar phenomenon was observed during the AIDS pandemic where behaviors that prevented transmission where more likely to be adopted in areas with higher prevalence of cases (Ahituv et al., 1996) and when one knew someone who had died of AIDS (Macintyre et al., 2001). Although various anecdotal media reports during the COVID-19 pandemic corroborate the view that close exposure to victims changes attitudes toward vaccination, to the best of our knowledge the issue has not received systematic empirical scrutiny.[3]

In this study, we deploy various data sources from England to explore this issue. We use spatial data on vaccination take-ups and COVID-19-related deaths measured at an unusually high geographic granularity and document several interesting patterns. First, cumulative vaccination take-up as of November 2021 is positively associated with COVID-19-related deaths that occurred before the vaccination program's rollouts. This is true controlling for demographic, economic, and health-related (e.g., mortality rates and flu vaccination coverage) features of the localities and geographic fixed effects at a higher level of disaggregation than our main spatial unit of analysis, which is the neighborhood. A set of placebo tests provides support for our identifying assumption that COVID-19-related mortality is conditionally exogenous.

Then, we investigate whether social proximity to victims underpins the impact of mortality on vaccination. Indeed, Funk et al. (2009) showed that social networks can suppress the spreading of a contagious disease by raising awareness and promoting protective behavior. To examine this, we ask whether members of ethnic minority groups who are, on average, more vaccine hesitant are swayed more strongly by information about deaths that occur in their local area. We expect this to be the case because ethnic minorities are *close-knit communities* in which social cohesion and network ties tend to be stronger compared to those among the white majority (Battu et al., 2011, Patacchini & Zenou, 2012, Eubank, 2019, Martén et al., 2019). Thus, the information about a community member's death is likely to circulate more quickly and efficiently among ethnic communities. That is, ethnic minorities who live in localities with higher presence of own-ethnicity people are more likely to be exposed to news about a COVID-19-related death that has occurred within their community.

We find that the share of ethnic minorities in a locality is negatively associated with vaccination rates. Moreover, localities with large share of ethnic minorities increase their vaccination rates as they get more exposed to COVID-related-deaths. In particular, we estimate that the interquartile change in death rates (which corresponds to a change of 7 deaths within a Middle Layer Super

[3]For instance, the quote in the epigraph is from a New York Times article reporting on a couple who had refused to get vaccinated until the husband caught the virus and was fighting for his life. Similar stories have been reported in the UK (https://www.theguardian.com/world/2021/jul/26/covid-patients-tell-of-regrets-over-refusing-jab-vaccine-intensive-care) and Australia (https://www.theage.com.au/national/victoria/leon-stingas-won-t-be-there-to-pick-the-veggies-he-planted-just-weeks-ago-20210930-p58w1u.html).

Output Area (MSOA)) leads to about 1 percentage point change in vaccination rates (corresponding to about 82 vaccinations per MSOA) in localities with a high presence of ethnic minorities (60%). We also find that larger death rate shocks—in the top tercile of the distribution—have stronger effects on vaccination rates. Our results are robust to a battery of sensitivity and robustness checks where we consider alternative functional forms, definitions of ethnicity, and measures of vaccinations and COVID-19 deaths.

We buttress this analysis with evidence on vaccination intention at the individual level using a nationally representative survey of the UK population. The survey collected information about the vaccination intentions of participants in November 2020 (before the vaccination rollout), which we exploit in this part of our analysis. The results corroborate the findings from the local-level analysis that members of ethnic minorities are less likely to vaccinate and that the gap in willingness to vaccinate between whites and ethnic minorities closes up as the death rate in the locality where they live increases. We can also explore further heterogeneity analysis of the positive interaction effect between ethnic minority and death rate. In particular, we find that the effect is driven by members of the ethnic minority aged below 50 and those ethnic groups that display a lower intention to vaccinate. We also find that the effect is more pronounced for ethnic minorities embedded in a larger local network of co-ethnics. This is consistent with the idea that closer proximity to someone who has died from COVID-19 increases the probability of vaccinating.

We then develop a simple Bayesian model where unvaccinated individuals update their prior about the expected benefits of vaccination by receiving a noisy signal. We show that they are more likely to get vaccinated the more they interact with vaccinated individuals in their neighborhood since the latter can provide precise and reliable information about the benefits of vaccination. We also explain why ethnic minorities may be reluctant to get vaccinated because they may have a higher cost or a lower benefit of getting vaccinated due the negative narratives about vaccination that circulate among closed-knit ethnic groups. We are also able to explain why deaths in a given location may positively affect its vaccination rate. Indeed, an increase in deaths in a given location increases the cost of non-vaccination and thus reduces that of vaccination and also increase the expected benefits of vaccination. Finally, we show that the impact of "negative" peers, that is, peers who are against vaccination, may be reduced if death rate increases in a given location. Indeed, when the latter occurs, the unvaccinated individuals update their beliefs about the benefits and costs of vaccination and thus pay less attention to negative peers.

This study is related to the literature on the determinants of vaccination take-up, which has examined several factors that we review here very selectively. Philipson (1996), Oster (2018), and Schaller et al. (2019) find that childhood disease prevalence and outbreaks increase infant and child vaccination rates in the US. Several studies have shown that the spreading of information that discredits vaccines by politically motivated entities or the mass media can affect immunization rates (Ander-

berg et al., 2011, Chang, 2018, Loomba et al., 2021, Carrieri et al., 2019, Qian et al., 2020, Martinez-Bravo & Stegmann, 2022, Hansen & Schmidtblaicher, 2021). More specific to the COVID-19 context, vaccination take-up has been shown to vary in function of socioeconomic and demographic characteristics (Robinson et al., 2020) and has been linked to traits such as individualism (Bian et al., 2022), prosociality (Reddinger et al., 2022) and psychological characteristics (Murphy et al., 2021). On the policy front, Karaivanov et al. (2022) show that government vaccination mandates do affect vaccine uptake, while Barber & West (2022) and Campos-Mercade et al. (2021) find that offering monetary incentives increases vaccination rates. In a cross-country analysis, Auld & Toxvaerd (2021) find that initial vaccination rates are not associated with total COVID-19 deaths on the eve of the rollout. To the best of our knowledge, ours is the first study that examines the impact of COVID-19 mortality on vaccination at the local level and to provide suggestive evidence of the underlying channel.

2 Background and Data

2.1 COVID-19 pandemic and vaccination rollout in the UK

In this section, we provide a brief timeline of the COVID-19 pandemic and vaccination rollout in the UK.

The first UK COVID-19 cases were recorded in late January 2020, while the first fatality occurred in early March 2020. Soon after, the government announced a national lockdown. In early April 2020, at the peak of the first wave of the pandemic, the country was recording more than 1,000 daily deaths. By the end of November 2020, the UK had recorded more than 60 thousand deaths related to COVID-19.

The UK was the first country to approve a COVID-19 vaccine in early December 2020; the vaccination program began on 8 December. The vaccine was offered at vaccination centres and pharmacies and appointments could be made online or through a GP surgery, so vaccines were widely available, and access was reasonably easy. The rollout proceeded in two main phases: in phase one, which was concluded in mid April 2021, vulnerable groups were prioritized, that is, people above 50 in a staggered way starting from the most senior ones (above 80), frontline health and social care workers, and individuals with underlying health conditions (about 31.8 million). A total of 32.5 million individuals had received a first dose by the end of the first phase (15 April 2021). In the second phase, the vaccine was made available to younger age groups (about 21 million) in a staggered way, so that the vaccine was offered to all adults in the UK by the end of July 2021. On 1 November, 2021, the total number of individuals that had received the first dose surpassed the 50 million mark, amounting to 87% of the population aged 12 and over (https://coronavirus.data.gov.uk/details/vaccinations).

2.2 Data

Local data. For the local-level analysis, we gathered data at the Middle Super Output Area (MSOA) level for England from various sources. MSOA is a small geographic area with an average population of about 8,000. MSOAs are quite uniform regarding population size, making them ideal for a local-level analysis. A map of MSOAs of England is presented in Figure A1 in Appendix A; key features of MSOAs are reported in Table A1. Table A2 contains data sources and links for all variables used in the local-level analysis.

We obtained data on vaccination from the National Health Service (NHS) England; counts of COVID and non-COVID related deaths come from the Office for National Statistics (ONS). Data on population by age groups were obtained from the 2019 ONS mid-year population estimates, which cover the "pre-pandemic" period July 2018 to June 2019. Counts of populations by ethnic group for all MSOAs in England were obtained from the last available Census (2011). Finally, we obtained data on the 2019 Index of Multiple Deprivation (IMD) from the website mySociety.[4]

Our main outcome for the local-level analysis is the vaccination rate, defined as the cumulative number of first-dose vaccinations between 8 December, 2020, and 25 November, 2021, divided by the total population in the MSOA. The two key explanatory variables are the ethnic share and the COVID-19 death rate. Ethnic share is the fraction of ethnic minorities in the MSOA population. Ethnic minorities are defined as persons who report ethnicity different than white. The COVID-19 death rate is defined as the cumulative count of deaths from COVID-19 between March and November 2020 over total population in the MSOA. Note that data on vaccinations and COVID-19 deaths—at this granular level—are not available by ethnicity.[5]

We present summary statistics of the MSOA-level data in Table 1. As of 25 November, 2021, the vaccination rate was 75.2%. The COVID-19 death rate was 0.001; a comparison with deaths for all other causes (0.007) provides an immediate measure of the relatively large impact that COVID-19 had at the local level for just nine months. The data show that, on average, one out of seven persons in each MSOA belongs to an ethnic minority. This table also contains summary statistics of the other variables used in the analysis.

Individual data. For the individual-level analysis, we accessed data from the safeguarded version of the Understanding Society COVID-19 survey, a special survey that explores individuals' experiences during the COVID-19 pandemic (University of Essex. ISER, 2021).[6] The survey was conducted

[4]The IMD data at MSOA level were constructed as part of a joint project between the University of Sheffield, the Ministry of Housing, Communities & Local Government and mySociety.

[5]Data on vaccinations by ethnicity are only available at the regional level; deaths from COVID-19 by ethnicity are only available at the country level.

[6]The complete survey reference is: "The Understanding Society: COVID-19 Study, 2020-2021", University of Essex, Institute for Social and Economic Research. Data can be accessed at https://www.understandingsociety.ac.uk.

Table 1: Summary statistics – MSOA data

	Mean	SD
Vaccination Rate - 1^{st} dose	0.752	0.088
Vaccination Rate - 2^{nd} dose	0.638	0.077
COVID-19 Death Rate	0.001	0.001
Share of Ethnic Minority	0.137	0.180
% Aged 16-29	0.167	0.072
% Aged 30-49	0.258	0.046
% Aged 50-64	0.194	0.036
% Aged 65-79	0.138	0.050
% Aged 80+	0.052	0.022
Index of Multiple Deprivation	0.216	0.132
Seasonal Flu Vaccination Rate	0.178	0.052
Non-COVID Death Rate	0.007	0.003
2015-2019 Death Rate	0.007	0.002

N=6,789. Vaccination take-up rate is the cumulative number of first dose vaccinations between 8^{th} December 2020 and 25^{th} November 2021 divided by total population in the MSOA.

COVID-19 Death Rate is defined as the cumulative number of COVID-19 deaths between 1^{st} March 2020 and 30^{th} November 2020 in the MSOA divided by total population in the MSOA.

Ethnic Exposure is defined as the % of ethnic minorities in the MSOA population.

The age variables represents the % of each group in the MSOA population.

Seasonal Flue Vaccination Rate refers to the vaccination rate of the seasonal flu for the period 2019/2020, defined as the total number of vaccinations over the population in the MSOA

The Index of Multiple Deprivation is based on 39 indicators and covers seven domains of deprivation: Income; Employment; Health Deprivation and Disability; Education, Skills Training; Crime; Barriers to Housing and Services; Living Environment. The score is divided by 100 for ease of interpretation.

Non-COVID Death Rate is defined as the cumulative number of deaths not attributed to COVID-19 between March 2020 and November 2020 in the MSOA divided by total population in the MSOA.

2015-2019 Death Rate refers to the average death rate between 2015 and 2019 referred to the interval March-November of each year.

monthly starting from April 2020 until July 2020, and every other month from September 2020 onward.

Our analysis focuses on the question about vaccination intentions asked in the November 2020 wave: "Imagine that a vaccine against COVID-19 was available for anyone who wanted it. How likely or unlikely would you be to take the vaccine?" This question was answered on a four-item scale (Very likely, Likely, Unlikely, Very unlikely). Note that this question was asked at a time when a clear plan about vaccinations did not yet exist.[7] Our outcome of interest is vaccine intention, defined as a binary variable equal to 1 if the answer to the vaccination intentions were "Very Likely" or "Likely" and 0 otherwise. In additional results, we also used data on actual vaccinations obtained from the March 2021 wave. We defined a dummy variable for vaccinations based on the question "Have you had a coronavirus vaccination?" with answers "Yes, first vaccination only," "Yes, both vaccinations," and "No, but I have an appointment" coded as 1 and 0 otherwise.[8]

3 Empirical Method

We are interested in estimating the relationship between vaccination rates and COVID-19-related deaths within localities (MSOAs). Our specification takes the form:

$$Y_l = \beta_0 + \beta_1 CovidDeath_l + X_l\gamma + LAD + \epsilon_l, \tag{1}$$

where Y_l is the vaccination rate in locality l. $CovidDeath_l$ denotes the COVID-19 death rate, which corresponds to the ratio between the number of deaths related to COVID in locality l and the population in the area. X_l is a vector of controls at the locality level (non-Covid death rate, age shares, ethnic shares, deprivation index, etc.), LAD are local authority district fixed effects, and ϵ_l is the error term.[9]

Our analysis relies on cross-sectional variation for identification. The main threat for the causal interpretation of the main parameter β_1 is reverse causality, as it may well be that vaccination rates are driving COVID-19-related deaths when the two are measured contemporaneously. This is precisely the reason why we use deaths that occurred before vaccines were rolled out, that is, deaths that occurred between March and November 2020. A second concern is the possible presence of unobservable area characteristics or shocks that might be confounding our estimates of the effect of

[7] Note that questions on vaccination intentions are also asked in the waves of January 2021 and March 2021 of the Understanding Society COVID-19 survey. We do not use data from these waves because vaccination intentions could be influenced by actual vaccine behavior, potentially confounding the impact of the local shock.

[8] Note that at the time of the survey (March 2020), vaccinations were available mainly for individuals aged 50 and above.

[9] Local Authority Districts (LADs) are administrative entities (there are 307 in England) that are supersets of MSOAs. The median number of MSOAs per LAD is 26. See Table A1 in Appendix A for further statistics. We used LAD indicators in our regressions to account for all unobservable factors at this level that might affect vaccinations in each MSOA.

deaths on vaccination rates. To address this, we use a range of locality-level characteristics including demographic structure and socio-economic deprivation, alongside measures of health status (mortality rate) and of the demand for preventive care (flu vaccination coverage). Thus, our identifying assumption is that, conditional on the rich set of controls included in X_l and the local authority fixed effects, COVID-19-related deaths are quasi-randomly assigned across localities. Figure A3 in Appendix A shows the distribution of the residualized COVID death rate, that is, the residuals obtained from a regression of the death rate on all other covariates of the regression in Table 2 Column I, including the LAD fixed effects. The figure illustrates that, after removing the impact of these observables, the distribution of death still exhibits a fair amount of variation and that such variation is close to that of a normal distribution.

In principle, one could construct a panel with the locality-month acting as unit of observation and use data on deaths that occurred after the rollout of vaccines in December 2020 in an attempt to estimate panel data models that account for locality unobserved time-invariant heterogeneity at the MSOA level. However, this would be a questionable approach as clearly deaths that occur after the vaccination program was launched are affected by vaccination up-take and can no longer be considered as conditionally exogenous. Indeed, Kim & Lee (2022) find that infections and deaths are negatively associated with vaccination rates across a sample of 8 countries.

As a check of our identification, we performed two placebo tests. The first follows a randomization-based inference procedure where we randomly reassigned to each locality the death rate of a neighbouring locality. This exercise, reported in Section 4.2, indicates that our results are "extreme/unusual" with respect to a distribution of coefficients generated by chance, providing support for the causal interpretation of our results. The second is a falsification test, in which we check whether COVID-19-related deaths explain preventive health behavior that occurred ahead of the pandemic. Specifically, we estimated Equation (1) on the fraction of women aged 25—49 who underwent cervical screening out of eligible women in the MSOA and on the vaccination rate related to three different child immunization programmes. We find that COVID-19-deaths have no statistically significant association with these outcomes.

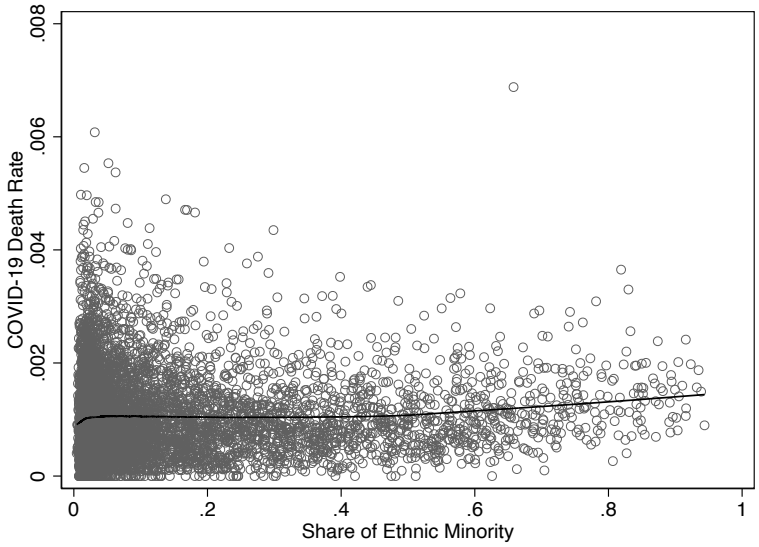
To examine whether there is heterogeneity in the impact of COVID deaths related to the concentration of ethnic minority groups in an area, we estimate an augmented specification, which includes an interaction between the COVID-19-death rate and the share of ethnic minorities $MinShare_l$ in a locality:

$$Y_l = \beta_0 + \beta_1 CovidDeath_l + \beta_2 MinShare_l + \beta_3 \left(CovidDeath_l \times MinShare_l\right) + X_l\gamma + LAD + \epsilon_l. \tag{2}$$

The main parameter of interest is β_3, which tells us whether localities with higher presence of ethnic minority groups respond to local death rate differently. To avoid a bias that arises from the fact that

the share of ethnic minority might be correlated with unobserved area characteristics, we use the ethnic composition of localities measured ten years earlier. Figure 1 shows that there is no systematic relationship between the share of ethnic minority and COVID-19-related deaths at the MSOA-level.

Figure 1: COVID-19 Death Rate and Ethnic Exposure – Locally weighted regression



The graph represents locally weighted regressions of COVID-19 Death Rate on Ethnic Exposure. Each circle represents a MSOA.

When using individual data, we estimate the following specification:

$$Y_i = \beta_0 + \beta_1 CovidDeath_l + \beta_2 Min_i + \beta_3 \left(CovidDeath_l \times Min_i\right) + Z_i\delta + X_l\gamma + LAD + \epsilon_i, \quad (3)$$

where Y_i is an indicator denoting whether individual i has expressed an intention of receiving the vaccine. Min_i is an indicator denoting whether individual i belongs to an ethnic minority. Z_i is a vector of controls at the individual level (gender, age, education, health status, marital status, etc.), while X_l are locality-level controls as in Equation (1). We cluster standard errors at the MSOA level, which is the level at which death rates are measured. The main parameter of interest here is β_3, which reveals whether ethnic minorities' willingness to vaccinate is affected differently by deaths than that of whites.

4 Locality-Level Evidence

4.1 Main results

We present our primary results in Table 2 based on the estimations of equations (1) and (2) in which the outcome of interest is the vaccination rate at the MSOA level. The first result that emerges in Column I is that there exists a positive and statistically significant relationship between death rates and vaccination rates ($p < 0.01$). This suggests that people are affected by deaths that occur near them when deciding to vaccinate. Regarding magnitude, a one standard deviation increase in the death rate in the neighborhood (0.1 percentage points or about 8 people) is associated with an increase in the vaccination rate by about 0.25 percentage points or about 21 additional vaccinations. Second, we observe that localities with higher share of ethnic minorities have a lower vaccination rate ($p < 0.01$), a pattern that has also been documented elsewhere (Razai et al., 2021, Robertson et al., 2021).[10] In particular, a 10 percentage point increase in the share of ethnic minority in a locality is associated with about 0.5 percentage point reduction in the vaccination rate. For the other predictors of COVID-19 vaccination, we find them to have the expected signs and to be statistically significant: higher shares of older groups are associated with more vaccination, and more deprived areas experience less vaccination, while areas with higher flu vaccination coverage have also higher vaccination rates. However, we find that the death rate due to causes unrelated to COVID-19 lack a statistically significant association with COVID-19 vaccination rates.

Share of ethnic minorities. In the second column, we examine the heterogeneity of the impact of the death rate with respect to the size of the ethnic minority groups. We find that the interaction term is positive and statistically significant, indicating that the impact of death rates on vaccination is larger in localities with higher share of ethnic minority groups. A very similar effect is obtained in Column III where, instead of controlling for non-COVID-related deaths during the pandemic, we control for the pre-pandemic mortality rate. Figure 2 offers a visual quantification of this effect: the two lines trace out the predicted vaccination rate (obtained from the estimates in Column II) as a function of the share of ethnic minority for death rates at the 25th and 75th percentiles of the distribution, respectively. We observe that, in localities with a high presence of ethnic minorities, say at 60%, the interquartile change in death rates leads to about 1 percentage point change in vaccination rates (corresponding to about 82 vaccinations per MSOA). We postulate that the reasons behind the stronger reaction to deaths by ethnic minorities are twofold: first, the fact that they are, on average, more hesitant than whites makes it easier to detect an effect, and, second, they have tighter social networks through which dramatic news such as the passing of a co-ethnic travel quickly. We provide

[10] In the UK, ethnic minorities have been disproportionately affected by the COVID-19 pandemic in terms of hospitalizations and deaths, economically (Platt & Warwick, 2020), and in terms of mental health deterioration (Proto & Quintana-Domeque, 2021).

Table 2: COVID-19 Deaths and Vaccination Rate

	1	2	3
COVID-19 Death Rate	2.477***	2.556***	2.183**
	(.845)	(.884)	(.908)
	[.021]	[.021]	[.018]
Share of Ethnic Minority	−.048***	−.054***	−.053***
	(.008)	(.008)	(.008)
	[−.098]	[−.109]	[−.108]
COVID-19 Deaths × Share of Ethnic Minority		18.210***	18.335***
		(6.545)	(6.545)
		[.026]	[.026]
% Aged 16-29	.169***	.178***	.175***
	(.035)	(.035)	(.035)
% Aged 30-49	.296***	.304***	.299***
	(.059)	(.058)	(.059)
% Aged 50-64	.704***	.702***	.698***
	(.058)	(.058)	(.059)
% Aged 65-79	.741***	.746***	.745***
	(.044)	(.044)	(.044)
% Aged 80+	.121*	.130*	.091
	(.067)	(.067)	(.072)
Index of Multiple Deprivation	−.227***	−.227***	−.230***
	(.008)	(.008)	(.009)
Seasonal Flu Vaccination Rate	.255***	.255***	.255***
	(.029)	(.029)	(.029)
Non-COVID Death Rate	.375	.421	
	(.369)	(.368)	
2015-2019 Death Rate			.865*
			(.462)
Local Authority District Fixed Effects	Yes	Yes	Yes
N	6,789	6,789	6,789
R^2	.76	.76	.76

Robust standard errors in parentheses. Standardized coefficients are presented in square brackets. The variables for the main effects of the interactions have been re-centered; hence, the coefficients refer to their mean value.

The dependent variable is vaccination rate in the Middle Super Output Area (MSOA), defined as the cumulative number of first dose vaccinations between 8^{th} December 2020 to 25^{th} November 2021 divided by total population in the MSOA.

COVID-19 Death Rate is defined as the cumulative number of COVID-19 deaths between 1^{st} March 2020 and 30^{th} November 2020 in the MSOA divided by total population in the MSOA.

Non-COVID Death Rate is defined as the cumulative number of deaths not related to COVID between 1^{st} March 2020 and 30^{th} November 2020 in the MSOA divided by total population in the MSOA.

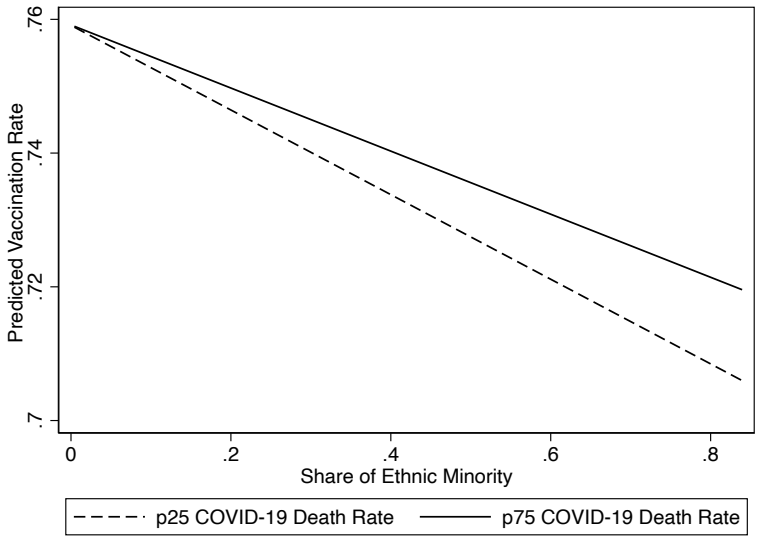
2015-2019 Death Rate is defined as the average yearly death rate from all causes between January 2015 and December 2019 in the MSOA divided by total population in the MSOA.

The age variable represents the % of each group in the MSOA population. The Index of Multiple Deprivation is the score divided by 100.

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

suggestive evidence in support of the network channel using the individual-level data in Section 5.

Figure 2: Predictions of Vaccination Rates by Different Values of COVID-19 Deaths



The graph represents predictions of the vaccination rate based on the estimates from the regression model in Table 2 column II for different values of the Share of Ethnic Minority (X-axis) and different values of COVID-19 Death Rate (dotted line: 25^{th} percentile; continuous line: 75^{th} percentile.)

Size of local death rate. One might expect that the impact of the mortality rate on vaccination is larger in areas that have experienced a heavier burden of deaths. In Table 3, we explore such heterogeneity. Columns I and II contain results of the same specification as in the respective columns of Table 2 using dummies for the terciles of the COVID-19 death rate distribution instead of a linear term. We find that the localities that experienced death rate in the highest tercile are associated with an increase in vaccination rate of 0.4 percentage points relative to localities in the lowest tercile ($p < 0.05$). Furthermore, for the share of ethnic minority gradient, we observe that a differential positive effect exists only in localities experiencing a death rate in the third tercile ($p < 0.01$). In the last two columns, we then split the sample into MSOAs with share of ethnic minority below (Column III) and above (Column IV) the median value, respectively. The results reveal that the positive effect of the share of ethnic minority in the MSOAs experiencing high deaths (3^{rd} tercile) is present only in localities with above median share of ethnic minority ($p < 0.01$). This analysis thus indicates that the simultaneous presence of a high death rate and a large ethnic community in an area induce a stronger positive relationship between COVID-19 mortality and vaccinations.

Table 3: Size of the Local Shock

	1	2	3	4
Share of Ethnic Minority	−.048***	−.066***	−.210*	−.047***
	(.008)	(.011)	(.111)	(.014)
	[−.098]	[−.135]	[−.039]	[−.106]
2^{nd} Tercile COVID-19 Deaths	.001	.001	.006	−.003
	(.002)	(.002)	(.014)	(.003)
	[.004]	[.005]	[.046]	[−.017]
3^{rd} Tercile COVID-19 Deaths	.004**	.004**	−.008	−.006*
	(.002)	(.002)	(.015)	(.003)
	[.022]	[.021]	[−.058]	[−.031]
2^{nd} Tercile COVID-19 Deaths × Share of Ethnic Minority		.004	.040	.013
		(.010)	(.124)	(.013)
		[.004]	[.033]	[.019]
3^{rd} Tercile COVID-19 Deaths × Share of Ethnic Minority		.032***	−.109	.054***
		(.011)	(.135)	(.014)
		[.041]	[−.091]	[.087]
N	6,789	6,789	3,395	3,394
R^2	.76	.76	.71	.72

Robust standard errors in parentheses. Standardized coefficients are presented in square brackets. The variables for the main effects of the interactions have been re-centered; hence, the coefficients refer to their mean value.

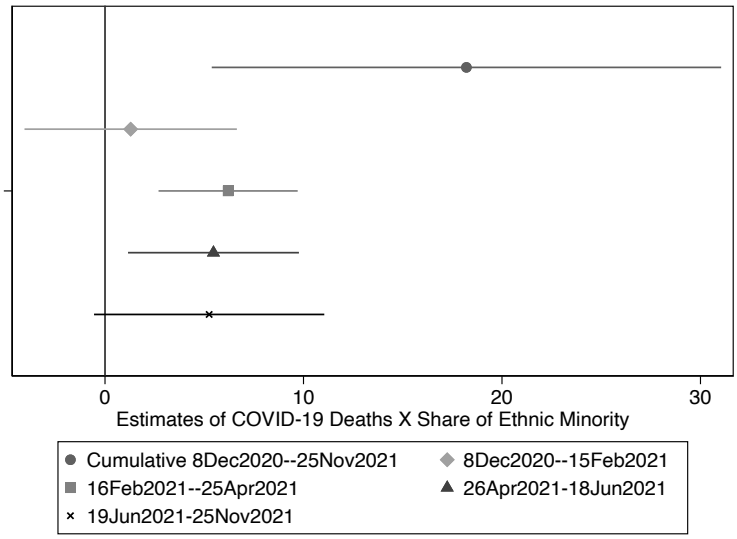
Columns I and II are the same specification of the corresponding models in Table 2 using tercile of COVID-19 Death Rate instead of the continous variable.

Columns III and IV are the same specification of Column I but on the substes of MSOA with Share of Ethnic Minority below (Column III) and above (III) the median value.

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

Timing. To examine what happens when younger cohorts become eligible, we exploit the fact that the vaccination program was rolled-out in phases, prioritizing older age groups first. In particular, we partitioned the period of the vaccination campaign that we examine—starting in December 2020 and ending in November 2021—to four phases that correspond to when the vaccine became available to different age groups: for 70+ (8^{th} Dec to 15^{th} Feb); for 50+ (16^{th} Feb to 25^{th} April); for 30+ (26^{th} April to 18^{th} June); and for 18+ (19^{th} June to 25^{th} November). This analysis is presented in Figure 3, which plots the coefficient and the confidence interval of the interaction between share of ethnic minority and death rate that we obtain from estimating Equation (2) for the whole period and for each of the 4 sub-periods separately. The pattern that emerges is that the 70+ cohort is inelastic with respect to the death rate, which was what we might expect from the group that is the most vulnerable in the population. The younger cohorts show similar positive reaction to the death rate, with the 50 to 70 group showing a slightly larger and more precisely estimated response than the two remaining younger cohorts, though the coefficients are not statistically distinguishable.

Figure 3: Timing of the Effect



The graph represents the coefficient estimates and confidence intervals for the interaction variable COVID-19 Deaths × Share of Ethnic Minority from the regression model in Table 2 Column II estimated both for the full period (Cumulative 8Dec2020-25Nov2021) and for different time intervals representing key phases of the COVID-19 vaccination program.

4.2 Robustness and placebo tests

Robustness. In our robustness analysis, we first assess whether our results are sensitive to the functional form and measures of deaths and vaccinations used in our baseline estimation of equation (2). These checks are presented in Table A4 in Appendix A and largely confirm our findings. In the first column, we estimate a log-log specification that also includes a control for total population. In Column II, we construct vaccination rates using the number of administered second doses. Both tests confirm our results. In the last two columns, we provide results using alternative measures of death rates: in Column III, we measure the "relative" COVID-19 death rate as the fraction of COVID- 19 deaths over deaths for all causes in each MSOA; in Column IV, we define the COVID-19 death rate as the difference between total deaths (for all causes) between March and November 2020 and the average number of deaths that took place in these months for 2015-2019. We then divide this by the population in the MSOA to obtain a measure of death rate. Both robustness checks confirm our main results.

The second type of robustness analysis we perform is to check whether our results are sensitive to how we measure the presence of ethnic groups. This analysis is presented in Table A5 in Appendix A. We find that the results are robust to a different definition of the white ethnic group that includes

only the white British. We also find that the response to death rate is stronger in localities that are more ethnically diverse (as measured by a Herfindahl index) and that have higher ethnic density (measured as the total non-white ethnic population divided by the MSOA area in hectares).

One might wonder if a similar pattern of results would be observed if we focused on the prevalence of COVID-19 cases instead of deaths. In Table A6, we report estimates of the same specifications reported in Table 2, replacing death rate by case rate. We find a similar pattern as above: cases are positively associated with vaccination rates, and areas with larger concentration of ethnic minorities have a stronger positive and statistically significant reaction.

Placebo tests. We perform two placebo tests as checks of our identification strategy. The first placebo test is reported in Figure A2. In this test, we perform randomization inference whereby we permute the value of the COVID-19 death rate with values from other MSOAs within the same LAD. We then simulated 5,000 regressions of the model in Table 2 Column I and obtained a set of estimates that we compared with our baseline estimates of COVID-19-death rate from Column I of Table 2. If our results were not driven by chance, we would have expected the simulations to generate estimates exceeding our baseline in only rare occasions. This is indeed what the results of this test show since no simulation produced a larger estimate than our baseline estimate.

In the second set of placebo tests reported in Table A3, we test the correlation between the COVID-19 death rate and the outcome from public health screening and immunization programs, which pre-date the beginning of the pandemic. Specifically, we consider the MSOA coverage of the NHS cervical screening program for the period 2019-2020, defined as the fraction of women aged 25 to 49 who underwent screening out of all eligible women of the same age. We also consider the vaccination rate related to three child immunization programs: seasonal flu, Meningococcal B (MenB), and Rotavirus. We define vaccination rates as the number of vaccinations in each MSOA over total population.[11] The rationale of these placebos is to provide a proxy for preventive health behavior at the MSOA level that (i) pre-dates the pandemic and thus should not be affected directly or indirectly by COVID-19 death rates in the locality and, (ii) arguably does not influence COVID-19 death rates, which were driven mainly by individuals of old age, while these programs mainly concern groups, which are not among the most vulnerable to COVID-19. The results of these placebo tests indicate no statistically significant association between COVID-19 death rate and any of these outcomes, providing additional reassurance that the MSOA-level COVID-19 death rate can be considered conditionally exogenous for the scope of our analysis.

[11]Note that screening and vaccination data are available at the Practice (GP) level. The counts at the MSOA level have been obtained by re-proportioning the GP-level counts using the share of patients from each practice that pertains to an MSOA, which was derived using the number of patients registered at a GP practice by LSOA of residence.

5 Individual-Level Evidence

We next turn attention to results obtained using the individual-level data to estimate Equation (3). These are presented in Table 4. Recall that the dependent variable here is the intention to vaccinate. In Column I, we find that, consistent with the locality-level analysis, ethnic minorities have lower intention to vaccinate. In Column II we see that the intention to vaccinate of ethnic minorities increases with the size of the local COVID-19 death rate faster than that of the majority group ($p < 0.1$). To gain a sense of the size of this effect, for an ethnic minority, an interquartile increase in the death rate (0.084) induces a nearly 4.9 percentage points higher probability of declaring an intention to vaccinate. Considering that the ethnic gap in vaccination intention is 16.1 percentage points (Column 1 of Table 4), this implies a closing of the ethnic gap in vaccinations by almost one-third.

Heterogeneity. In the analysis so far, we have classified all ethnic minorities into the same group. In Column III, we look at the heterogeneity of the effect for ethnic minorities of different age groups relative to whites of all ages. What we find is that the younger age group (under 50) is the most responsive: an interquartile increase in the death rate increases their vaccination intention probability by about 7.1 percentage points ($p < 0.01$), whereas, for the older age group (over 50), the effect is negative but not statistically significant. The second split that we perform in Column IV is to classify ethnic groups into two subgroups based on their average intention to vaccinate. We thus create two subgroups, one containing those ethnic groups that have the *lowest intention* (White and Black Caribbean, Pakistani, Bangladeshi, Caribbean, African, Any Other Black, Arab) and another containing the rest of the ethnic minority groups. We find that for individuals belonging to the low-intention group, there is evidence of a positive reaction to the death rate relative to whites ($p < 0.01$), with an interquartile increase in the death rate increasing the vaccination intention probability by about 8.6 percentage points. However, for the high-intention group, the effect is negative but again not statistically significant. This pattern suggests that the vaccination decision of groups or individuals that are more hesitant to start with is more likely to be influenced by deaths.

Ethnic minorities and social proximity. We next zoom in on ethnic minorities to perform some additional analysis and to probe why they have a stronger reaction to the local death rate.

One shortcoming of the data is that we do not observe deaths by ethnicity at the local level. However, at the individual level, we can approximate the social proximity to someone who might have died due to COVID. We do this by interacting the local death rate by the size of one's own ethnicity group in the locality. This analysis is reported in Table 5. We find that ethnic minorities living in areas with larger own-ethnic groups are more positively affected by the death rate. This is consistent with the idea that a larger network makes it more likely that if a member of their own ethnic group has died, they are informed about it.

Table 4: COVID-19 Deaths and Vaccination Intentions – Microdata Evidence

	1	2	3	4
MSOA COVID-19 Death Rate (× 100)	.048	−.038	−.041	−.059
	(.125)	(.120)	(.119)	(.120)
Ethnic Minority	−.161***	−.166***		
	(.035)	(.035)		
MSOA COVID-19 Death Rate (×100)× Ethnic Minority		.623*		
		(.361)		
Ethnic Minority Age 16-49			−.164***	
			(.041)	
Ethnic Minority Age 50+			−.170***	
			(.051)	
MSOA COVID-19 Death Rate (×100)× Ethnic Minority Age 16-49			.895***	
			(.337)	
MSOA COVID-19 Death Rate (×100)× Ethnic Minority Age 50+			−.267	
			(.602)	
Ethnic Minority Low Vaccination Intentions				−.287***
				(.046)
Ethnic Minority High Vaccination Intentions				−.043
				(.040)
MSOA COVID-19 Death Rate (×100)× Ethnic Minority Low Vaccination Intentions				1.077***
				(.389)
MSOA COVID-19 Death Rate (×100)× Ethnic Minority High Vaccination Intentions				−.281
				(.500)
Local Authority District Fixed Effects	Yes	Yes	Yes	Yes
N	7,955	7,955	7,955	7,955
R^2	.21	.21	.21	.22

Robust standard errors clustered at the MSOA level in parentheses.
Regressions are weighted using cross-sectional individual web survey weights.
The dependent variable is a binary variable for vaccination intention. This is based on the question "Imagine that a vaccine against COVID-19 was available for anyone who wanted it. How likely or unlikely would you be to take the vaccine?" with answers "Very Likely" and "Likely" coded as 1 and answers Unlikely and Very Unlikely coded as 0.
MSOA COVID-19 Death Rate is defined as the cumulative number of COVID-19 deaths between 1^{st} March 2020 and 30^{th} November 2020 in the MSOA divided by total population in the MSOA. Values are multiplied times 100 for ease of interpretation.
High Vaccination Intentions include the following ethnic groups: White and Black Caribbean, Pakistani, Bangladeshi, Caribbean, African, Any Other Black, Arab.
Low Vaccination Intentions include the following ethnic groups: White and Black African, White and Asian, Any Other Mixed Background, Indian, Chinese, Any Other Asian Background, Any Other Ethnic Group.
The regression includes the following control variables at the individual level: dummies for gender, quinary age groups, being in a partnership, having kids in school age, having elderly in the household, having poor health, being foreign-born, having a degree, having no qualifications, being employed, receiving Universal Credit; income and a dummy for missing income. The regression includes the following covariates at the MSOA level: % Aged 16-29, % Aged 30-49, % Aged 50-64, % Aged 65-79, % Aged 80+, Share of Ethnic Minority, Index of Multiple Deprivation, Seasonal Flu Vaccination Rate and Non-COVID Death Rate.
* $p < 0.10$.; ** $p < 0.05$.; *** $p < 0.01$.

Table 5: Additional Results on Ethnic Minorities

	Intentions		Vaccinations	
MSOA COVID-19 Death Rate (× 100)	.975**	2.152***	.839*	1.644**
	(.447)	(.538)	(.482)	(.716)
Size of Ethnic Network		−.035		−.006
		(.029)		(.027)
MSOA COVID-19 Death Rate × Size of Ethnic Network		.573***		.434*
		(.190)		(.241)
N	851	851	581	581
R^2	.56	.57	.69	.69

Robust standard errors clustered at the MSOA level in parentheses.
Regressions are weighted using cross-sectional individual web survey weights.
The dependent variable in the first two columns is a binary variable for vaccination intention. This is based on the question "Imagine that a vaccine against COVID-19 was available for anyone who wanted it. How likely or unlikely would you be to take the vaccine?" with answers "Very Likely" and "Likely" coded as 1 and answers Unlikely and Very Unlikely coded as 0.
The dependent variable in last two columns is a binary variable for vaccination take-up in March 2021. This is based on the question 'Have you had a coronavirus vaccination?' with answers Yes, first vaccination only, Yes, both vaccinations and No, but I have an appointment coded as 1 and 0 otherwise.
Size of Ethnic Network is defined as the log number of individuals of the same ethnicity living in the MSOA. The ethnic groups considered are: White, White and Black Caribbean, White and Black African, White and Asian, Other Mixed, Pakistani, Indian, Bangladeshi, Chinese, Other Asian, African, Caribbean, Other Black, Arab, Any other ethnic groups.
The regression includes all the covariates of Table 4.
* $p < 0.10$.; ** $p < 0.05$.; *** $p < 0.01$.

To further support this argument, we present some evidence that social interactions are more intensive for ethnic minorities in Table 6. The table draws statistics from Waves 3 and 6 of Understanding Society. While there are no sharp differences between the white and ethnic minorities in terms of average number of friends, the table shows that the individuals in the latter group are more likely to engage in activities and discuss issues with their close network of friends. This evidence suggests that the information about a community member's death is more likely to circulate more quickly and efficiently among ethnic communities.

Actual Vaccination. Finally, note that so far we have presented results for intentions to vaccinate prior to the rollout of the program. For a subset of individuals, we can look into actual vaccination as of March 2021, three months into the program. We repeat the analysis discussed above using actual vaccination in the last two columns of Table 5. Reassuringly, the results are consistent, although the sample is slightly smaller.

Table 6: Social Network Characteristics by Ethnicity

	White		Ethnic Minority	
	Mean	SD	Mean	SD
Number of Named Friends	2.719	0.579	2.528	0.711
Share of Ethnic Minority Friends	0.031	0.122	0.783	0.344
Number of Activities done with Friends	0.431	2.952	8.359	9.791
Number of Issues Discussed with Friends	0.438	2.997	8.465	9.905

Source: Understanding Society Wave 3 and 6.
N: 63,836 (White); 9595 (Ethnic Minority)
Ethnicity is defined as non-white ethnic groups
Number of Activities done with Friends refer to the number of activities done with each named friends, averaged over the number of named friends. The activities include: travel or take holidays together, watch sport, watch other tv, go to films, concerts or other events, just talk, web chat, go to pubs, cafes or clubs, go shopping, do sport or other types of exercise together, do other hobbies or activities together, eat together.
Number of Issues Discussed with Friends refer to the number of issues discussed with each named friends, averaged over the number of named friends. The topics include: tv, relationships, food & drink, travel, music, sport, work, politics, religion, family or children, books, magazines, other hobbies or interests, films

6 A Possible Mechanism

Let us now develop a simple Bayesian-updating model of vaccination that provides a possible mechanism of our results.

6.1 Model

Consider a finite number of locations. Each location is populated by a continuum of individuals. As in our empirical analysis, there are two types of individuals: those who are *vaccinated* and those who are *not vaccinated*. Accordingly, we define an individual's type θ as follows: $\theta \in \{V, NV\}$, where NV and V stand, respectively for "Vaccinated" and "Non-Vaccinated".

In each location, there are vaccinated and unvaccinated individuals. We want to study how, in each location, the decision to be vaccinated for an unvaccinated individual is affected by the percentage of *vaccinated individuals* residing in the same location. Let $p \equiv \mathbb{P}\{\theta = V\}$ be the share of vaccinated individuals in a given location. We refer to p as the *vaccination exposure rate*. All unvaccinated individuals do not precisely know the true benefit b of getting vaccinated; thus, b is a *random* variable that follows a normal distribution $b \sim \mathcal{N}\left(\beta, \sigma_b^2\right)$, where $\beta > 0$ is the mean and $\sigma_b^2 > 0$ is the variance. In other words, the expected benefit of getting vaccinated is equal to β. Importantly, when an unvaccinated individual meets a vaccinated or an unvaccinated individual, he/she receives a noisy signal s_θ about the benefit of getting vaccinated. This signal has the following standard structure

$$s_\theta = b + \varepsilon_\theta, \tag{4}$$

where ε_θ is an error term that follows a normal distribution $\varepsilon_\theta \sim \mathcal{N}\left(0, \sigma_\theta^2\right)$, with $\mathrm{Cov}(b, \varepsilon_\theta) = 0$. The key idea of our model is that vaccinated individuals are better informed about the benefits of vaccination and can therefore convinced their unvaccinated peers to get vaccinated. This implies that

$\sigma^2_{NV} > \sigma^2_V$, which means that vaccinated individuals can convey a more precise information about vaccination than unvaccinated individuals, that is, the signal about the benefit of getting vaccinated is less noisy.

We now describe the vaccination behavior of an unvaccinated individual. Define Δ as a binary variable, where $\Delta = 1$ means that an unvaccinated individual gets vaccinated, while $\Delta = 0$ implies non-vaccination. Then, the probability of an unvaccinated individual getting vaccinated is given by:

$$\mathbb{P}\{\Delta = 1\} = p\,\mathbb{P}\{\Delta = 1 \,|\, \theta = V\} + (1-p)\,\mathbb{P}\{\Delta = 1 \,|\, \theta = NV\}, \tag{5}$$

where $\mathbb{P}\{\Delta = 1 \,|\, \theta = V\}$ is the probability of getting vaccinated conditional on meeting a vaccinated individual, while $\mathbb{P}\{\Delta = 1 \,|\, \theta = NV\}$ is the probability of getting vaccinated conditional on meeting an unvaccinated individual. We can easily verify that

$$\frac{\partial \mathbb{P}\{\Delta = 1\}}{\partial p} > 0 \quad \Longleftrightarrow \quad \mathbb{P}\{\Delta = 1 \,|\, \theta = V\} > \mathbb{P}\{\Delta = 1 \,|\, \theta = NV\}. \tag{6}$$

In other words, there is a positive relationship between p, the proportion of vaccinated individuals in a given location, and $\mathbb{P}\{\Delta = 1\}$, the individual probability of an unvaccinated individual getting vaccinated if and only if interacting with a vaccinated individual is more beneficial for vaccination than interacting with an unvaccinated individual.

6.2 Predictions

Assume that all individuals are risk-neutral. Define z, the net payoff, as follows:

$$z := \begin{cases} b - c, & \text{if } \Delta = 1, \\ 0, & \text{if } \Delta = 0, \end{cases} \tag{7}$$

where $c > 0$ is the fixed cost of getting vaccinated. We have the following utility function:

$$U_\theta(\Delta) := \mathbb{E}\,[z \,|\, s_\theta] = \begin{cases} \mathbb{E}\,(b \,|\, s_\theta) - c, & \text{if } \Delta = 1, \\ 0, & \text{if } \Delta = 0. \end{cases} \tag{8}$$

Risk neutrality implies that only the expected difference between the benefit and cost of vaccination matters. For $\theta = \{V, NV\}$, using (8), the conditional probabilities defined in equation (5) are given by

$$\mathbb{P}\{\Delta = 1 \,|\, \theta\} = \mathbb{P}\{\mathbb{E}\,(b \,|\, s_\theta) > c\}, \tag{9}$$

where $\mathbb{E}\,(b \,|\, s_\theta)$ is the expected benefit of getting vaccinated for an unvaccinated individual conditional on receiving signal s_θ. All individuals of type θ are Bayesian in the sense that they update

their prior expectations β about the benefits of vaccination after receiving the signal s_θ to posterior expectations $\mathbb{E}(b \mid s_\theta)$, which is a convex combination of β and s_θ where the weights are $\frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_b^2}$ and $\frac{\sigma_b^2}{\sigma_\theta^2+\sigma_b^2}$, respectively.[12] We have the following predictions:[13]

Proposition 1.

(i) The higher is the cost of vaccination and/or the lower is the expected benefit from vaccination, the lower is the probability of an unvaccinated individual to get vaccinated, that is,

$$\frac{\partial \mathbb{P}\{\Delta = 1\}}{\partial c} < 0, \qquad \frac{\partial \mathbb{P}\{\Delta = 1\}}{\partial \beta} > 0.$$

(ii) Assume that $c > \beta$ and $\sigma_{NV}^2 > \sigma_V^2$. Then, the vaccination rate of unvaccinated individuals increases with the vaccination exposure rate, that is,

$$\frac{\partial \mathbb{P}\{\Delta = 1\}}{\partial p} > 0.$$

(iii) Assume that $c > \beta$ and $\sigma_{NV}^2 > \sigma_V^2$. Then, the higher is the cost of vaccination and/or the lower is the expected benefit from vaccination, the higher is the impact of the vaccination exposure rate on the vaccination rate of unvaccinated individuals, that is,

$$\frac{\partial^2 \mathbb{P}\{\Delta = 1\}}{\partial p \partial c} > 0, \qquad \frac{\partial^2 \mathbb{P}\{\Delta = 1\}}{\partial p \partial \beta} < 0.$$

Part (i) of Proposition 1 shows that when the cost of vaccination increases, quite naturally, individuals become more reluctant to get vaccinated. This result can explain what we found in Table 2 (and Table 4), that is, the fact that ethnic minorities are less likely to get vaccinated. Indeed, it is possible that the cost of vaccination is higher for ethnic minorities because they are more skeptical about the benefit of vaccination due to bad experiences they had in the past with public action. It is also possible that there is a narrative among ethnic minorities that the COVID 19 virus is a "hoax" and that the government uses vaccination to control people. Both explanations would increase the cost of vaccination. This result can also explain why we found in Table 2, that is, the fact that death rate in a given location increases vaccination rate. Indeed, an increase in death rate increases the expected benefits β or decreases the cost c of vaccination because individuals realize that if they become infected with COVID 19, they can die from it. Consequently, they update their beliefs about the expected benefits (or cost) of vaccination and get more vaccinated.

[12] See Equation (B.1) in Appendix B.
[13] The proof of Proposition 1 can be found in Appendix B.

Part (ii) of Proposition 1 shows that if $c > \beta$ and $\sigma^2_{NV} > \sigma^2_V$, the higher is the fraction of vaccinated individuals in a given location, the more likely unvaccinated individuals interact with vaccinated individuals and the higher chance an unvaccinated individual gets vaccinated. Before explaining the intuition of this result, let us comment on these two assumptions. First, $\sigma^2_{NV} > \sigma^2_V$ is at the heart of our model. It says that vaccinated individuals are better informed about the benefits of vaccination than unvaccinated individuals and can therefore better convinced their unvaccinated peers to get vaccinated because they can provide a more precise (or less noisy) information about the benefits of vaccination. Second, $c > \beta$ is assumed to make the problem interesting otherwise the expected benefit of vaccination for a risk-neutral unvaccinated individual will be too high compared to the cost and unvaccinated individuals will get vaccinated even in the absence of interactions with vaccinated individuals. Indeed, looking at the formula (B.3) in Appendix B of the probability of getting vaccinated conditional of meeting an individual of type $\theta \in \{V, NV\}$, we see that if $c < \beta$, the quantity in bracket will always be negative and thus individuals will always get vaccinated.

Let us now comment on the result displayed in part (ii) of Proposition 1. When p increases, the unvaccinated individuals are more likely to meet a vaccinated individual, who has more precise information about the benefit of vaccination. Thus, unvaccinated individuals will update their beliefs about vaccination and will thus be more likely to get vaccinated.

Finally, part (iii) of Proposition 1 shows the cross effect of peers and vaccination cost/benefit on vaccination rate. It can explain the positive cross effect of peers and death found in Table 2. Indeed, when c decreases or β increases due to an increase in deaths in a given location,[14] the impact of vaccinated peers on the probabilty of getting vaccinated decreases, since unvaccinated individuals do not need as much information about the benefits of vaccine. In Table 2, we show that when deaths increase, the negative effect of ethnic peers on vaccination is smaller, which is consistent with our result since ethnic minorities tend to be less vaccinated.

7 Conclusion

In recent years, many countries are witnessing a rising trend in vaccination refusal and hesitancy that is being associated with outbreaks of vaccine-preventable diseases; this has raised serious concerns among public health officials (Larson et al., 2014, Phadke et al., 2016, De Figueiredo et al., 2020, Sallam, 2021). The rapid development and rolling-out at scale of the vaccine for COVID-19 has been hailed as a major breakthrough in the global fight against the pandemic. Despite the initial optimism, vaccine take-up has been far from universal–especially among racial and ethnic minorities–even in countries with large supply. Understanding what drives the decision of resisting vaccination is imperative for informing current public health interventions, especially considering the protracted

[14] Indeed, when deaths increase, the cost of *non-vaccination* increases and thus the cost of *vaccination* decreases. The same reasoning can be applied to expected benfits.

impact of the COVID-19 pandemic. It is also relevant for improving the preparedness and ability of the national health services to tackle similar situations of public health emergency that might occur in the future. In this study, we contribute to the discussion by providing evidence that COVID-19 mortality measured locally induces demand for vaccination in England, in particular, for ethnic minority groups. We conjecture that this finding is explained by the fact that ethnic communities are more tightly connected; thus, when a community member falls victim of the disease, the news spreads quickly and strongly affects other community members. In other words, social proximity to victims of the disease can trigger an urgency to take protective measures against it.

Our findings suggest that, to encourage vaccination among hesitant groups, vaccination campaigns should aim at facilitating the diffusion of information among members of highly hesitant groups about the actual local impact of the disease—that the vaccine is designed to eliminate—at the neighborhood or community level. This could be achieved, for instance, by mobilizing influential members of these communities (e.g., community leaders) or families of patients and victims.

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Appendix

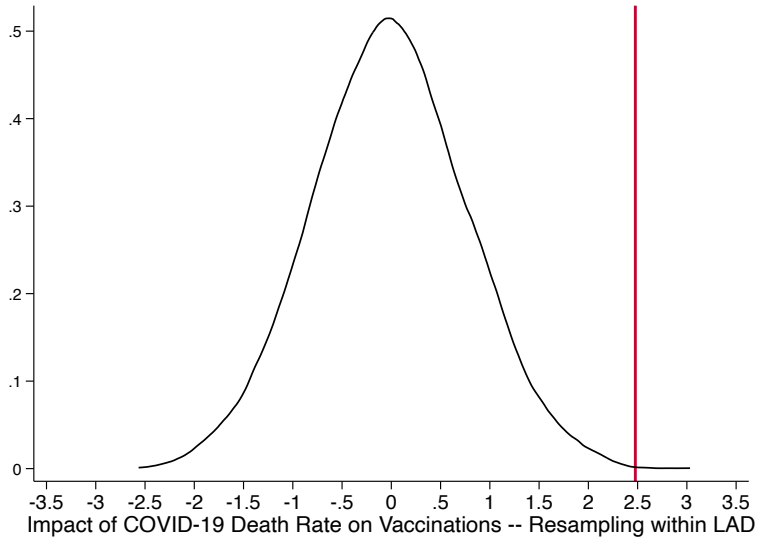
A Appendix: Additional Tables and Figures

Figure A1: Maps of MSOAs

MSOAs in England (light lines) and London boundaries (dark lines)

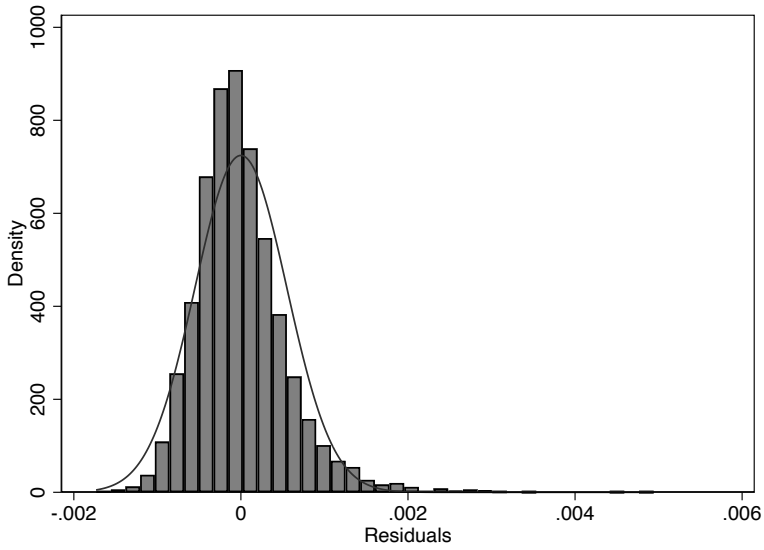
MSOAs (light lines) and LADs (dark lines) in London

Figure A2: Placebo: Randomization Inference



The graph represents the coefficient estimates for variable COVID-19 Deaths from simulations of the regression model in Table 2 column I where the variable COVID-19 Deaths has been permuted with values from other MSOA in the same LAD. N=5,000 permutations.

Figure A3: Density of Residualized Death Rate



The graph represents the distribution of the residuals from a regression of COVID-19 Death Rate on all MSOA covariates included in Table 2 Col II, including LAD fixed effects.

Table A1: Key Characteristics of MSOAs and LADs

	MSOA	**LAD**
Number	6,789	307
Avg. Population	8,067	178,403
Avg. Area (in 10,000 m^2)	1,958	43,298

Due to small numbers the figures for two MSOAs (City of London and Isles of Scilly have been combined with other MSOAs). This results in having 6,789 instead of 6,791 MSOAs forming England.

Table A2: Sources of MSOA-level data

Data	Year	Source	Link	Last accessed
Vaccinations	2020/2021	NHS England	https://www.england.nhs.uk/statistics/statistical-work-areas/covid-19-vaccinations/covid-19-vaccinations-archive/	29/11/2021
Ethnicity	2011	ONS Census	https://www.nomisweb.co.uk	29/11/2021
COVID and non-COVID Deaths	2020	ONS Deaths involving COVID-19 by local area and deprivation	https://www.ons.gov.uk/file?uri=%2Fpeoplepopulationandcommunity%2Fbirthsdeathsandmarriages%2Fdeaths%2Fdatasets%2Fdeathsduetocovid19bylocalareaanddeprivation%2Fapril2021/covidlocalareadeprivationapril2021.xlsx	29/11/2021
Population / Age	2018/2019	ONS Population Estimates	https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/middlesuperoutputareamidyearpopulationestimates	29/11/2021
Index of Multiple Deprivation	2019	Ministry of Housing, Communities & Local Government / University of Sheffield / mySociety	https://research.mysociety.org/sites/imd2019/about/	29/11/2021
Cervical Screening Coverage	2019/2020	NHS Digital	https://digital.nhs.uk/data-and-information/publications/statistical/cervical-screening-programme/cervical-screening-programme-coverage-statistics-management-information#related-links	29/11/2021
Vaccination Programmes: Childhood Flu, Meningococcal B (MenB), Rotavirus, Seasonal Flu	2019/2020	NHS Digital	https://digital.nhs.uk/data-and-information/publications/statistical/gp-contract-services/2018-19/gpprac1819	29/11/2021

Table A3: Placebo Regressions

	Cervical Screening	Children Vaccinations		
		Influenza	Men B	Rotavirus
COVID-19 Death Rate	.486	.021	.060	.037
	(.574)	(.040)	(.097)	(.030)
	[.005]	[.006]	[.006]	[.013]
Seasonal Flu Vaccination Rate	.378***	.022***	.012**	.004**
	(.016)	(.001)	(.005)	(.002)
	[.272]	[.415]	[.093]	[.090]
N	6,789	6,789	6,789	6,789
R^2	.86	.58	.67	.65

Robust standard errors in parentheses. Standardized coefficients are presented in square brackets.

COVID-19 Death Rate is defined as the cumulative number of COVID-19 deaths between 1^{st} March 2020 and 30^{th} November 2020 in the MSOA divided by total population in the MSOA.

Cervical Screening: The dependent variable is the coverage of the Cervical Screening Programme in the MSOA, defined as the fraction of women aged 25-49 who underwent cervical screening out of eligible women aged 25-49 in the MSOA.

Children Vaccinations: The dependent variable is the vaccination rate of one of the three programmes (Childhood seasonal influenza vaccination programme, Meningococcal B (MenB) infants vaccination programme, Rotavirus vaccination programme) defined as the number of children who received the vaccine between 01 April 2019 to 31 March 2020 divided by the MSOA population.

The counts of screenings/vaccination comes at GP-level; counts at MSOA level have been obtained by reproportioning the GP-level counts using the % of patients from each practice that pertains to an MSOA which was derived using the number of patients registered at a GP practice by LSOA of residence.

The regression contains all covariates of Table 2 Column I, including LAD fixed effects.

$^{*}\ p < 0.10.$; $^{**}\ p < 0.05.$; $^{***}\ p < 0.01.$

Table A4: Robustness Checks

	1	2	3	4
COVID-19 Death Rate	.003**	2.286***	.013**	.686
	(.001)	(.794)	(.005)	(.419)
	[.011]	[.022]	[.020]	[.010]
Share of Ethnic Minority	−.115***	−.077***	−.050***	−.050***
	(.013)	(.007)	(.008)	(.008)
	[−.093]	[−.179]	[−.101]	[−.103]
COVID-19 Deaths × Share of Ethnic Minority	.035***	18.301***	.082*	7.023**
	(.010)	(5.812)	(.042)	(3.366)
	[.021]	[.030]	[.016]	[.016]
N	6,789	6,789	6,789	6,789
R^2	.93	.75	.76	.76

Robust standard errors in parentheses. Standardized coefficients are presented in square brackets. The variables for the main effects of the interactions have been re-centered, hence the coefficients refer to their mean value.

Col I: Same as model in Column II of Table 2, but using log vaccinations in the MSOA instead of vacccination rate as depdendent variable, log COVID-19 deaths in the MSOA instead of death rate as main independent variable. The regression also includes a control for log population in the MSOA.

Col II: Same as model in Column II of Table 2, but the dependent variable refers to the second dose only.

Col III: Same as model in Column II of Table 2, but COVID-19 Death Rate is calculated as the total COVID-19 deaths over the total deaths (for all causes). This model does not include the Non-COVID Death Rate as control variable.

Col IV: Same as model in Column II of Table 2, but COVID-19 Death Rate is calculated as excess death, that is the difference between total deaths (for all causes) over the period 1^{st} March to 30^{th} November 2020 minus the average death rate for the years 2015-2019 referred to the same month interval (March-November). This model does not include the Non-COVID Death Rate as control variable.

$^{*}\ p < 0.10.$; $^{**}\ p < 0.05.$; $^{***}\ p < 0.01.$

Table A5: Alternative Ethnicity Definitions

	Exposure No W.B.	Ethnic Diversity	Ethnic Density
COVID-19 Death Rate	2.947***	1.455	2.264***
	(.884)	(.896)	(.872)
	[.025]	[.012]	[.019]
Alternative Ethnicity Definition	−.080***	.015	−.031***
	(.007)	(.030)	(.011)
	[−.194]	[.007]	[−.064]
COVID-19 Deaths × Alternative Ethnicity Definition	15.115***	71.678**	14.996**
	(5.123)	(35.440)	(7.551)
	[.025]	[.023]	[.019]
N	6,789	6,789	6,789
R^2	.77	.76	.76

Robust standard errors in parentheses. Standardized coefficients are presented in square brackets. The variables for the main effects of the interactions have been re-centered, hence the coefficients refer to their mean value.

Exposure No W.B: Same as model in Column II of Table 2, but Share of Ethnic Minority refers to all ethnic groups excluding White British.

Ethnic Diversity: Same as model in Column II of Table 2, but using the Herfindal Index instead of Share of Ethnic Minority. The Herfindal Index is defined as the sum of the square of the shares of each non-white ethnic group. The non-white ethnic groups are: White and Black Caribbean, White and Black African, White and Asian, Other Mixed, Indian, Pakistani, Bangladeshi, Chinese, Other Asian, African, Caribbean, Other Black, Arab, Any other ethnic groups

Ethnic Density: Same as model in Column II of Table 2, but using Ethnic Density instead of Share of Ethnic Minority. Ethnic Density is defined as the total non-white ethnic population divided by MSOA area in hectars.

$^{*}\ p < 0.10.$; $^{**}\ p < 0.05.$; $^{***}\ p < 0.01.$

Table A6: COVID-19 cases and vaccination

	1	2	3
COVID-19 Cases Rate	1.474***	1.374***	1.377***
	(.125)	(.129)	(.131)
	[.249]	[.232]	[.232]
Share of Ethnic Minority	−.080***	−.094***	−.094***
	(.008)	(.011)	(.011)
	[−.164]	[−.192]	[−.192]
COVID-19 Cases Rate × Share of Ethnic Minority		.823***	.823***
		(.313)	(.312)
		[.035]	[.035]
Local Authority District Fixed Effects	Yes	Yes	Yes
N	6,786	6,786	6,786
R^2	.77	.77	.77

Robust standard errors in parentheses. Standardized coefficients are presented in square brackets. The variables for the main effects of the interactions have been re-centered, hence the coefficients refer to their mean value.

The dependent variable is vaccination rate in the Middle Super Output Area (MSOA), defined as the cumulative number of first dose vaccinations between 8^{th} December 2020 to 25^{th} November 2021 divided by total population in the MSOA. COVID-19 Cases is the cumulative number of cases between 7^{th} March 2020 to 30^{th} November 2020 in the MSOA divided by total population in the MSOA.

The regression includes all other controls of the corresponding columns of Table 2.

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

Table A7: Summary statistics – Microdata

	Mean	SD
COVID-19 Vaccine Intention	0.820	0.384
Female	0.533	0.499
Age	50.783	17.832
Has Partner	0.638	0.481
N. Children in School	0.365	0.788
Has Elderly in Household	0.145	0.353
Poor Health	0.039	0.192
Foreign Born	0.081	0.272
Has Degree	0.291	0.454
Has No Qualifications	0.053	0.225
Employed	0.601	0.490
Weekly Income in £	614.365	487.639
Receives Universal Credit	0.064	0.245
COVID-19 Death Rate ($\times$ 100)	0.102	0.071
Ethnic Exposure	0.119	0.167
MSOA % Aged 16-29	0.161	0.064
MSOA % Aged 30-49	0.256	0.045
MSOA % Aged 50-64	0.197	0.035
MSOA % Aged 65-79	0.142	0.049
MSOA % Aged 80+	0.054	0.022
MSOA Seasonal Flu Vaccination Rate	0.187	0.051
MSOA Index of Multiple Deprivation	0.201	0.123
MSOA Non-COVID Death Rate ($\times$ 100)	0.680	0.250

N=7,972. Statistics are weighted using cross-sectional individual web survey weights.

Income is expressed in £/1000.

COVID-19 Death Rate is defined as the cumulative number of COVID-19 deaths between 1^{st} March 2020 and 30^{th} November 2020 in the MSOA divided by total population in the MSOA.

Share of Ethnic Minority is defined as the % of ethnic minorities in the MSOA population.

The age variables represents the % of each group in the MSOA population.

Seasonal Flue Vaccination Rate refers to the vaccination rate of the seasonal flu for the period 2019/2020, defined as the total number of vaccinations over the population in the MSOA

The Index of Multiple Deprivation is based on 39 indicators and covers seven domains of deprivation: Income; Employment; Health Deprivation and Disability; Education, Skills Training; Crime; Barriers to Housing and Services; Living Environment. The score is divided by 100 for ease of interpretation.

Non-COVID Death Rate is defined as the cumulative number of deaths not attributed to COVID-19 between 1^{st} March 2020 and 30^{th} November 2020 in the MSOA divided by total population in the MSOA.

B Appendix: Proof of Proposition 1

Remember that (see (5)):

$$\mathbb{P}\{\Delta = 1\} = p\,\mathbb{P}\{\Delta = 1 \,|\, \theta = V\} + (1-p)\,\mathbb{P}\{\Delta = 1 \,|\, \theta = NV\}.$$

Thus, before proving the proposition, let us calculate $\mathbb{P}\{\Delta = 1\}$. Because of the normality assumptions of b and ε_θ, we have:

$$\mathbb{E}\left(b \,|\, s_\theta\right) = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_b^2}\beta + \frac{\sigma_b^2}{\sigma_\theta^2 + \sigma_b^2}s_\theta. \tag{B.1}$$

It is easily verified that

$$\mathbb{E}\left(b \,|\, s_\theta\right) \sim \mathcal{N}\left(\beta, \frac{\sigma_b^4}{\sigma_\theta^2 + \sigma_b^2}\right). \tag{B.2}$$

Using (B.2), (9) can be written as follows:

$$\mathbb{P}\{\Delta = 1 \,|\, \theta\} = 1 - \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_\theta^2}\right), \tag{B.3}$$

where

$$\Phi(x) := \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x} \exp\left(-\frac{y^2}{2}\right) \mathrm{d}y$$

is the cumulative distribution function of the standard univariate normal distribution. Hence,

$$\begin{aligned}
\mathbb{P}\{\Delta = 1\} &= p\,\mathbb{P}\{\Delta = 1 \,|\, \theta = V\} + (1-p)\,\mathbb{P}\{\Delta = 1 \,|\, \theta = NV\} \\
&= p\left[1 - \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_V^2}\right)\right] + (1-p)\left[1 - \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_{NV}^2}\right)\right] \\
&= 1 - p\Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_V^2}\right) - (1-p)\,\Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_{NV}^2}\right).
\end{aligned} \tag{B.4}$$

Using (B.3), this implies, in particular, that

$$\mathbb{P}\{\Delta = 1 \,|\, \theta = V\} - \mathbb{P}\{\Delta = 1 \,|\, \theta = NV\} = \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_{NV}^2}\right) - \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_V^2}\right). \tag{B.5}$$

Let us first prove (i)**:** By differentiating (B.4) and taking into account that $\Phi(\cdot)$ is an increasing function, we obtain:

$$\frac{\partial \mathbb{P}\{\Delta = 1\}}{\partial c} = -p\left(\frac{\sqrt{\sigma_b^2 + \sigma_V^2}}{\sigma_b^2}\right)\Phi'(.) - (1-p)\left(\frac{\sqrt{\sigma_b^2 + \sigma_{NV}^2}}{\sigma_b^2}\right)\Phi'(.) < 0. \tag{B.6}$$

Proceeding in a similar way, it is straightforward to show that $\frac{\partial \mathbb{P}\{\Delta=1\}}{\partial \beta} > 0$.

Let us now prove (ii)**:** Combining (B.5) with (6) and taking into account that $\Phi(\cdot)$ is an increasing function, we find that

$$\begin{aligned}\frac{\partial \mathbb{P}\{\Delta=1\}}{\partial p} &= \mathbb{P}\{\Delta=1 \,|\, \theta=V\} - \mathbb{P}\{\Delta=1 \,|\, \theta=NV\} \\ &= \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2+\sigma_{NV}^2}\right) - \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2+\sigma_V^2}\right).\end{aligned}$$

Thus, $\frac{\partial \mathbb{P}\{\Delta=1\}}{\partial p} > 0$ if and only if $c > \beta$ and $\sigma_{NV}^2 > \sigma_V^2$.

Let us finally prove (iii)**:** By differentiating (B.6) and taking into account that $\Phi(\cdot)$ is an increasing function, we obtain

$$\frac{\partial^2 \mathbb{P}\{\Delta=1\}}{\partial p \partial c} = \left(\frac{\sqrt{\sigma_b^2+\sigma_{NV}^2}}{\sigma_b^2}\right)\Phi'(.) - \left(\frac{\sqrt{\sigma_b^2+\sigma_V^2}}{\sigma_b^2}\right)\Phi'(.).$$

Thus, $\frac{\partial^2 \mathbb{P}\{\Delta=1\}}{\partial p \partial c} > 0$ if and only if $\sigma_{NV}^2 > \sigma_V^2$.

Proceeding in a similar way, it is straightforward to show that $\frac{\partial^2 \mathbb{P}\{\Delta=1\}}{\partial p \partial \beta} < 0$.