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Analyses of topical policy issues

Do disease prevalence and severity drive COVID-19 vaccine demand?

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Abstract

Large scale vaccination of population is widely accepted to be the key to recovery from the devastating economic and public health impacts of the COVID-19 pandemic. However, low uptake of vaccine has challenged vaccination efforts in many parts of the world. The paper explores the determinants of demand for COVID-19 vaccination – specifically, the prevalence dependence hypothesis – that identifies infection prevalence and mortality as the key drivers of individual preventive behavior against infectious diseases. Using daily disease tracking and vaccination data from 47 European countries the paper finds strong evidence that COVID-19 infection rate and mortality rate drive future vaccination uptake. Specifically, results from fixed effects models suggest that while lagged infection prevalence induce vaccination uptake by 0.18 to 0.24 percent, while the effect of lagged mortality is significantly larger, ranging between 1.10 to 1.53 percent. The results highlight the critical role of behavioral response to epidemiological outcomes and are of critical significance for COVID-19 mitigation policies, especially as they relate to achieving vaccine-induced herd immunity and economic reopening.

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1. Introduction

Achieving high vaccination coverage worldwide is essential for ending the current COVID-19 pandemic and setting up global economic recovery. However, ‘vaccine hesitancy’ and consequent low acceptance of vaccines, has emerged as a major barrier to increasing uptake in many parts of the world. Addressing the causes of low vaccine demand has now become a policy priority worldwide.

Determinants of demand for vaccines are numerous. However, recent surveys identified ‘complacency’ as the key driver of low vaccine acceptance (Cascini et al., 2021; Sallam, 2021). A person is subject to vaccination complacency when her perceived risks of a vaccine-preventable disease are so low that she deems vaccination unnecessary. Increases in disease prevalence and severity, however, can elevate perception of disease risk, thereby decreasing vaccine complacency, and in turn increasing vaccine uptake. This insight was originated in the ‘prevalence dependence’ hypothesis in the early economic epidemiology literature that suggested a positive link between perceived risk of infection as reflected in the infection rate in the population, and demand for vaccination (Philipson and Posner, 1993). Furthermore, the higher the disease mortality rate, the greater is the incentive to adopt preventive measures among the unvaccinated (Philipson, 2000). The prevalence-dependence hypothesis offers a sensible representation of rational human behavior around vaccination. However, whether and to what extent demand for vaccine is affected by the observed prevalence and severity of disease...
remains unclear. The paper aims to empirically investigate these questions using the global daily tracking and vaccination data on COVID-19.

The paper builds on the early work by Geoffard and Philipson (1996, 1997) and Philipson (2000) that spawned the subsequent economic-epidemiology literature attempting to incorporate endogenous prevention behavior. A growing number of studies have since integrated endogenous behavior into disease transmission models (Manfredi and D’Onofrio, 2013; Verelst et al., 2016; Weston et al., 2018). Several studies offer empirical estimates of prevalence dependent behavior against other infectious diseases. For example, Ahituv et al. (1996) find that one percent increase in the prevalence of AIDS increases the likelihood of contraceptive use by up to 50 percent. However, knowledge of partner’s HIV status and HIV prevalence are not found to increase subsequent contraceptive use or reduce women’s fertility in sub-Saharan Africa (Anglewicz and Clark, 2013; Magadi and Agwanda, 2010; Boucekkine et al., 2009). In the context of demand for vaccination, Philipson (1996) documents that demand for measles, mumps and rubella (MMR) vaccine increase with community prevalence of these diseases. Severity of disease is also a predictor of perceived risk from a vaccine-preventable disease. Mullahy (1999) finds a high correlation between mortality risk of influenza and demand for influenza vaccines among the elderly. In California, vaccination uptake against measles during 1988–90 followed media coverage of the outbreak that included number of infected and deaths (Dales et al., 1993). Intension to vaccinate self as well as own children increased with prevalence and mortality in the context of 2009 influenza pandemic in the US (SteelFisher et al., 2009).

However, how changes in perceived risk translates into change in vaccine demand remains to be understood in the context of the COVID-19 pandemic. There is a need to test the prevalence dependence hypothesis using reliable data and estimate the infection prevalence and fatality elasticities of demand for vaccines. Underlying uncertainty around risk of contracting a rapidly evolving SARS-CoV-2 virus and concurrent availability of effective vaccines affords a unique opportunity to this end.

The paper estimates the effects of past COVID-19 infection and mortality rates on vaccine uptake using a panel data on 47 European countries over July 02 to 29 December 2021 – a period when the European Union officially launched its ‘vaccine certificate’ program to encourage vaccine uptake. Thus, vaccine coverage was largely demand-driven in the sample period, although the results are immune to later start of the sample period for up to 8 weeks. The fixed-effects estimation results strongly validate the hypothesis: a one percentage increase in the COVID-19 infection rate and total COVID-19 mortality rate three weeks earlier, increases current vaccine uptake by 0.18 and 1.53 percent, respectively. These results are robust to different sample periods, model specifications, inclusion of indicators of local disease treatment capacity, and exclusion of outliers and small countries that may have had lingering issues with distribution of vaccines even as late as July 2021.

The results provide strong empirical evidence that preventive behavior against COVID-19, and similar infectious diseases, depends on observed epidemiological outcomes. This insight improves our understanding of the role of risk perception in vaccine hesitancy by quantifying the effects of disease contraction and mortality risks. The paper makes a strong case for integrating human response to epidemic into COVID-19 management policies. The results also have deep implications for mitigation and vaccination policies against any infectious disease, including COVID-19. First, a surge in disease prevalence is predicted to be self-limiting because it would endogenously increase vaccination uptake. Second, declining prevalence discourages vaccination uptake, allowing infections to return. Thus, even successful vaccination programs may find it difficult to eradicate the disease.

The rest of the paper is organized as follows. A simple heuristic model of rational vaccination decision is described in Section 2. Section 3 describes the data and estimation methods. The results are discussed in Section 4. Section 5 concludes the paper with a summary and implications for policy.

2. A rational vaccination decision

This section outlines a simple rational choice framework of private demand for prevention through vaccination against an infectious disease following Geoffard and Philipson (1996) and Auld (2006), who discuss demand for protection in the context of HIV infections. Suppose the utility function of an individual deciding whether to vaccinate or not is given by \( u(h, d) \) where the state variable \( h \) represents health status (infectious \((i)\) or susceptible \((s)\)), and \( d \) represents a binary indicator for protection \((d=1)\). For the individual, the likelihood of contracting the disease is given by the probability of randomly coming in contact with an infected person that results in a transmission. Let \( \beta \) be the probability that an infected individual transmits the virus to a susceptible on contact. Following the epidemiological principle of mass action, if the infection prevalence rate \( i \equiv I/N \) – i.e., the proportion of infected \((I)\) in the population of size \( N \) – represents the probability of a random contact occurring between a susceptible and an infected, the probability of the former contracting the virus from the latter is given by \( \beta I \).

An individual faces a positive probability of death that varies with \( h \): \( \{ p_i \text{ if } h = i; p_s \text{ if } h = s \} \), with \( 1 \geq p_i \geq p_s \geq 0 \). These conditional probabilities depend on death rates in the respective groups in the local population – that is, \( p_i \) is mortality rate among the non-infected individuals and \( p_s \) is the case-fatality rate, or the number of deaths as a proportion of the detected infection cases that varies with the epidemiological state of the outbreak. Since case-fatality rate is not

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1. See: [https://www.devex.com/news/covid-19-a-timeline-of-the-coronavirus-outbreak-96396](https://www.devex.com/news/covid-19-a-timeline-of-the-coronavirus-outbreak-96396).
always available or understandable to general population and given that individuals make decisions based on the available information, \( p_i \) is approximated by total COVID-19 fatality rate — that is the proportion of confirmed COVID-19 deaths in the population. For simplicity, assume that death is associated with a disutility of magnitude \( D \) regardless of health status.

Let the value function evaluated in the susceptible state be given by:

\[
V(s) = \max \left\{ u(s, 1) + \alpha \left[ V(s) - p_{i,t}D \right]; u(s, 0) + \alpha \left[ \beta i V(i) + (1 - \beta i) V(s) - p_{i,t}D \right] \right\}
\]

(1)

where \( i_t \) denotes the prevalence rate measured by proportion of infected in the population at time \( t \), \( \beta > 0 \) is the transmission probability, and \( \alpha > 0 \) is the discount factor. Eq. (1) depicts the utility trade-off a rational susceptible individual faces when deciding on vaccination. On the one hand, vaccination offers protection against being infected allowing a person to remain susceptible tomorrow and face a reduced chance of death. On the other hand, by failing to vaccinate the person not only risks becoming infected with a probability which increases in prevalence, but also risks death with a probability that increases with case fatality rate. This directly implies that the individual chooses not to vaccinate until the current benefit of not vaccinating outweighs the expected future loss due to risk of infection:

\[
d = 0 \iff u(s, 0) - u(s, 1) \geq \alpha \beta i_t [V(s) - V(i) - (p_{i,t} - p_{i,t})D]
\]

(2)

Propensity to vaccinate in an epidemic can therefore be characterized by two simple thresholds under which the individual engages in protection. First, a susceptible vaccinates if the infection prevalence exceeds a time-varying reservation prevalence, denoted by \( \hat{i} \). Following Geoffard and Philipson (1996), this reservation prevalence is obtained by solving the value function in Eq. (1) holding the probabilities of death constant, and is given by:

\[
d = 0 \iff i_t \leq \hat{i} \equiv \frac{1}{\beta} \left[ u(s, 1) - u(i, 0) + \alpha(p_{i,t} - p_{i,t})D \right]
\]

(3)

Furthermore, a susceptible vaccinates if the reported case-fatality rate exceeds a reservation probability of death, given by \( \hat{p}_i \). Thus, given everything else, the second threshold is given by:

\[
d = 0 \iff p_{i,t} \leq \hat{p}_i \equiv \frac{1}{\alpha D} \left[ \frac{u(s, 1) - u(s, 0)}{\beta i_t} - \frac{u(s, 1) - u(i, 0)}{\beta i} \right] + p_s
\]

(4)

Intuitively, the reservation prevalence in Eq. (3) and reservation fatality rate in Eq. (4) rise with the instantaneous cost of protection, \( u(s, 1) - u(s, 0) \), and fall with the cost of infection, \( u(s, 1) - u(i, 0) \), the probability of transmission conditional on exposure, and the increase in the expected cost of death when infected relative to when susceptible.

Based on these simple heuristics, we expect uptake of COVID-19 vaccine to increase with detected case numbers and reported death rates in the local population. The empirical model discussed below aims to estimate the responsiveness or the elasticities of vaccine uptake with respect to increase in infections and disease fatality in Europe.

3. Data and estimation strategy

The empirical analysis uses publicly available daily COVID-19 tracking data from 02 July 2021 to 29 December 2021 (180 days) on 47 European countries extracted from Our World in Data (OWID).\(^2\) Although vaccination in Europe started in December 2020, there were hindrances with vaccine procurement, supply, safety-related issues with certain vaccines, that affected vaccine rollout in Europe in the first few months of 2021. However, these issues were resolved by May

\(^2\) The dataset is freely available at: https://github.com/owid/covid-19-data/tree/master/public/data (accessed on December 31, 2021).
To study the prevalence dependence hypothesis, vaccination coverage is only limited by the demand side factors and therefore would represent an ideal sample timeline including the second half of 2021. Nevertheless, countries in this group exhibited substantial variation in vaccination rates. As of October 1, 2021, some countries like Ireland, Malta, Portugal, and Denmark fully vaccinated around 90 percent of their adult population, while for Romania and Bulgaria these numbers are only 33 percent and 22 percent, respectively. In absence of any significant supply constraint hindering inoculation program during the sample period, vaccination coverage is only limited by the demand side factors and therefore would represent an ideal sample to study the prevalence dependence hypothesis.

The empirical model to be estimated is given by:

$$y_{it} = \alpha_i + x_{it-j} \beta_{it-j} + \delta t + \epsilon_{it}, i = 1, \ldots, 47; j = 7, \ldots, 42; t = 1, \ldots, 180$$

where $y_{it}$ denotes new vaccinations per million population in country $i$ at date $t$; $\alpha_i$ captures the time-invariant, unobserved country-specific effects; $\beta_{it-j}$ are the slope coefficients of the regressors in the vector $x_{it-j}$, measured for $j = 7, 14, 21, 28, 35$, and 42 days. $\delta$ denotes the coefficient of a common linear trend, $t$. The residuals $\epsilon_{it}$ are assumed to be distributed identically and independently with zero mean and constant variance. The underlying assumption in the empirical model is that current vaccination uptake depends on past values of COVID-19 infection and fatality rates, other indicators of risks of infection and severity, proportion of people already vaccinated, and current degree of stringency.

| Table 2 | Determinants of new vaccination: Fixed effects estimation results at 21-day lag. |
|---------|------------------------------------------------------------------|
| New vaccinations (per mill.) ($t$) | Sensitivity test results |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| New cases (per mill.) ($t - 21$) | 0.24*** | 0.22*** | 0.18*** | 0.68*** | 0.72*** | 0.65*** |
| Total cases (per mill.) ($t - 21$) | 1.46*** | 0.98** | 0.39 | 1.05*** | 0.67*** | −1.35 |
| New deaths (per mill.) ($t - 21$) | −0.03 | −0.02 | 0.04 | −0.05 | −0.06 | −0.18*** |
| Total deaths (per mill.) ($t - 21$) | 0.15 | 1.10** | 1.53*** | 0.27 | 0.04 | 4.33*** |
| No. fully vaccd. (per hund.) ($t - 21$) | −1.04*** | −0.91*** | −3.24*** | −3.26*** | −3.70*** |
| Stringency index ($t$) | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| Weekly hosp. (per mill.) ($t - 21$) | −0.54*** | −0.38*** | −0.37*** |
| Weekly ICU (per mill.) ($t - 21$) | −0.17*** | −0.20*** |
| Total booster (per hund.) ($t - 21$) | −0.02 |
| Time (No. of days) | −0.00*** | −0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Constant | 179.63*** | 58.20 | 72.60 | −187.41*** | −208.27*** | −323.39*** |
| N (# of countries) | 7093 (47) | 5357 (46) | 4783 (41) | 1717 (20) | 926 (14) | 549 (13) |

Sensitivity test results

| (1) | (2) | (3) | (4) | (5) | (6) |
| 0.17*** | 0.32*** | 0.39*** | 0.04 | 0.06 | 0.08 |
| 32.76*** | 46.74*** | 72.74*** | 0.98** | 0.01*** | 0.01*** |
| 46.74*** | 72.74*** | 0.98** | 0.01*** | 0.01*** | 0.01*** |
| 72.74*** | 0.98** | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| 32.76*** | 46.74*** | 72.74*** | 0.98** | 0.01*** | 0.01*** |
| 72.74*** | 0.98** | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| 72.74*** | 0.98** | 0.01*** | 0.01*** | 0.01*** | 0.01*** |

All variables except Time are log-transformed. Coefficients are estimated using Driscoll–Kraay standard errors (reported in parentheses).

*p < 0.10.

**p < 0.05.

***p < 0.01.
of public health measures (denoted by the ‘stringency index’) that might either deter (transport or other access-related issues) or encourage (lower opportunity cost of foregone income) vaccination.

Descriptive statistics for the variables (in levels) are presented in Table 1. I use the smoothed series for population-normalized (per million) values of new vaccinations, new cases, and new deaths available in the OWID database. Stringency index is a composite measure of government-imposed restrictions including school and workplace closures, and travel bans, takes values between 0 (mildest) to 100 (harshest). In the OWID database, weekly intensive care unit (ICU) and hospital admissions reflect daily new admission numbers for a given week.

The panel is unbalanced due to countries adopting varying time frames for reporting epidemiological statistics. In panel data with long time-series, heteroscedasticity, cross-sectional dependence, and serial correlation are potential issues. Within Europe, country level data could be spatially correlated, which would render the commonly applied clustered estimation of standard errors invalid in standard fixed or random effects models (such as pooled or generalized least square models). Hence, I use the (Driscoll and Kraay, 1998) standard errors that allows robust fixed effects estimation with heteroscedasticity consistent standard errors that are robust to very general forms of spatial and serial correlations (Hoechle, 2007). A maximum autocorrelation lag of seven is used assuming that the residuals are autocorrelated for up to seven days.

4. Results

Table 2 presents the results of fixed effects estimation model where the key epidemiological variables are lagged by 21 days. Columns (1)–(3) show the main results – the estimated coefficients for three alternative specifications. All variables, except time trend are expressed in natural logarithm, which allows interpretation of the estimated coefficients as elasticities. Columns 4–6 display results for sensitivity tests discussed in Section 4.1.

Table 3
Determinants of new vaccination: Fixed effects estimation at 7–42-day lags.

| New vaccinations (per mill.) | Coeff (t−7)† | Coeff (t−14)† | Coeff (t−21)† | Coeff (t−28)† | Coeff (t−35)† | Coeff (t−42)† |
|------------------------------|--------------|--------------|--------------|--------------|--------------|--------------|
| New cases (per mill.)†       | 0.29***      | 0.24***      | 0.18***      | 0.11**       | 0.05         | 0.00         |
| Total cases (per mill.)†     | 2.17***      | 1.37***      | 0.39         | −0.51        | −1.29***     | −1.76***     |
| New deaths (per mill.)†      | −0.09        | −0.02        | 0.04         | 0.08*        | 0.12***      | 0.13***      |
| Total deaths (per mill.)†    | 1.48***      | 1.52***      | 1.53***      | 1.47***      | 1.58***      | 1.59***      |
| No. fully vaccd. (per hund.)†| −0.81***     | −0.87***     | −0.91***     | −0.85***     | −0.82***     | −0.77***     |
| Stringency index             | 0.01***      | 0.01***      | 0.01***      | 0.02***      | 0.02***      | 0.02***      |
| Time                         | −0.01***     | −0.01***     | −0.00        | 0.00         | 0.00         | 0.00         |
| Constant                     | 203.59***    | 147.64***    | 72.60        | 1.52         | −60.28       | −103.25***   |
| N (# of countries)           | 4785 (43)    | 4780 (42)    | 4783 (41)    | 4780 (41)    | 4775 (42)    | 4787 (42)    |
| Within R²                    | 0.38         | 0.35         | 0.33         | 0.30         | 0.29         | 0.29         |

All variables except Time are log-transformed.

*p < 0.10.
**p < 0.05.
***p < 0.01.
†Denotes corresponding lag (in days) for new cases (per million), new deaths (per million), no. fully vaccd. (per hundred), total cases (per million), and total deaths (per million). Coefficients are estimated using Driscoll–Kraay standard errors (reported in parentheses).

6 These series are smoothed using a seven-day moving average to adjust for the discrepancies in reporting intervals. The linearly interpolated daily series allows for cross-country comparisons over time. For more detail on smoothing and definition of the variables, see: https://github.com/owid/covid-19-data/tree/master/public/data.

7 The data on hospitalizations ICU admissions are provided by the European Centre for Disease Prevention and Control (ECDC) only for a select number of European countries and updated on a weekly basis.

8 The results are robust to inclusion of different autocorrelation lags. All results are available on request.
Table A.1
Vaccination start dates for the 47 European countries in the sample.
Source: Our World in Data [https://github.com/owid/covid-19-data/blob/master/public/data/owid-covid-data.csv].

| Country                  | First date of vaccination | No. of vaccinations (per million) on the date in col. 2 |
|--------------------------|---------------------------|--------------------------------------------------------|
| Albania                  | 11/01/2021                | 64                                                     |
| Andorra                  | 26/01/2021                | 66                                                     |
| Austria                  | 28/12/2020                | 1331                                                   |
| Belgium                  | 29/12/2020                | 35                                                     |
| Bulgaria                 | 30/12/2020                | 2889                                                   |
| Bosnia and Herzegovina   | 12/02/2021                | 574                                                    |
| Belarus                  | 29/12/2020                | 403                                                    |
| Switzerland              | 23/12/2020                | 214                                                    |
| Cyprus                   | 7/01/2021                 | 534                                                    |
| Czechia                  | 28/12/2020                | 2307                                                   |
| Germany                  | 28/12/2020                | 18109                                                  |
| Denmark                  | 11/02/2021                | 8021                                                   |
| Spain                    | 5/01/2021                 | 56505                                                  |
| Estonia                  | 28/12/2020                | 318                                                    |
| Finland                  | 1/01/2021                 | 459                                                    |
| France                   | 28/12/2020                | 486                                                    |
| United Kingdom           | 11/01/2021                | 165844                                                 |
| Greece                   | 29/12/2020                | 630                                                    |
| Croatia                  | 31/12/2020                | 1105                                                   |
| Hungary                  | 29/12/2020                | 6202                                                   |
| Ireland                  | 29/12/2020                | 68                                                     |
| Iceland                  | 31/12/2020                | 63                                                     |
| Italy                    | 28/12/2020                | 1502                                                   |
| Liechtenstein            | 6/01/2021                 | 1                                                       |
| Lithuania                | 28/12/2020                | 2797                                                   |
| Luxembourg               | 29/12/2020                | 348                                                    |
| Latvia                   | 18/12/2020                | 1                                                       |
| Monaco                   | 31/12/2020                | 126                                                    |
| Moldova                  | 6/03/2021                 | 520                                                    |
| North Macedonia          | 17/02/2021                | 189                                                    |
| Malta                    | 18/01/2021                | 1297                                                   |
| Montenegro               | 21/02/2021                | 223                                                    |
| Netherlands              | 7/01/2021                 | 6387                                                   |
| Norway                   | 18/12/2020                | 4                                                       |
| Kosovo                   | 29/03/2021                | 117                                                    |
| Poland                   | 29/12/2020                | 4300                                                   |
| Portugal                 | 28/12/2020                | 2791                                                   |
| Romania                  | 28/12/2020                | 1101                                                   |
| Russia                   | 16/12/2020                | 3357                                                   |
| San Marino               | 28/02/2021                | 120                                                    |
| Serbia                   | 9/01/2021                 | 1150                                                   |
| Slovakia                 | 5/01/2021                 | 885                                                    |
| Slovenia                 | 28/12/2020                | 1683                                                   |
| Sweden                   | 2021-01-04                | 9297                                                   |
| Ukraine                  | 2021-02-25                | 1179                                                   |

The dates in col. 2 and the numbers in col. 3 are based on the smoothed series in the original data source. These dates may differ from the dates of actual start of vaccination.

Columns (1)–(3) show that new cases significantly induce new vaccinations: a one percent increase in new cases total deaths per million people results in new uptake of vaccination by 0.18 percent three weeks later, as shown in column 3 that represents the most preferred model. Column 3 shows that the effects of total deaths are significantly larger with a positive ‘fatality elasticity of vaccination’ of 1.53. Taken together, these results lend support to the prevalence dependence hypothesis. In addition to infection prevalence, the results emphasize the role of severity of illness, measured by disease mortality, as a key determinant of the disease risk-perception that drives vaccination uptake, in line with Mullahy (1999).

4.1. Sensitivity test results

Uptake of vaccines may also respond to other risk factors, such as available treatment capacity in the local health system. For example, higher rates of hospital and ICU admissions may prompt vaccination uptake through increased perception of disease severity in the context of limited capacity of local health systems. To examine whether prevalence-dependence of vaccination is mediated by these considerations, I include data on new ICU admissions and hospitalization rates. Given the sample period includes rollout of ‘booster’ vaccination in some countries that may mechanically inflate vaccination uptake for certain population groups, the results are re-estimated controlling for total boosters administered.
Determination of new vaccination: Fixed effects estimation at 21-day lag (excluding the United Kingdom).

| New vaccinations (per mill.) (t) | Sensitivity test results |
|----------------------------------|--------------------------|
|                                  | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          |
| New cases (per mill.) (t - 21)   | 0.24***      | 0.23***      | 0.19***      | 0.69***      | 0.72***      | 0.65***      |
|                                  | (0.05)       | (0.05)       | (0.04)       | (0.06)       | (0.06)       | (0.14)       |
| Total cases (per mill.) (t - 21) | 1.02         | 0.56         | −0.41        | 0.92***      | 0.67*        | −1.35        |
|                                  | (0.63)       | (0.54)       | (0.50)       | (0.28)       | (0.36)       | (0.93)       |
| New deaths (per mill.) (t - 21)  | −0.02        | −0.01        | 0.06         | −0.03        | −0.06        | −0.18**      |
|                                  | (0.05)       | (0.05)       | (0.05)       | (0.04)       | (0.06)       | (0.08)       |
| Total deaths (per mill.) (t - 21)| 0.48         | 1.45         | 2.18**       | 0.23         | 0.04         | 4.33**       |
|                                  | (0.63)       | (0.59)       | (0.57)       | (0.39)       | (0.53)       | (1.03)       |
| No. fully vaccd. (per hund.) (t) | −1.00**      | −0.85***     | −3.15***     | −3.26**      | −3.70***     | −3.70***     |
|                                  | (0.22)       | (0.22)       | (0.34)       | (0.34)       | (0.43)       | (0.43)       |
| Stringency index (t) (t - 21)    | 0.02***      | 0.01***      | 0.01***      | 0.01***      |              |              |
|                                  | (0.00)       | (0.00)       | (0.00)       | (0.00)       |              |              |
| Weekly hosp. (per mill.) (t - 21)| ‒0.00        | 0.00         | −0.00        | −0.01***     | −0.01***     | −0.17**      |
|                                  | (0.00)       | (0.00)       | (0.00)       | (0.00)       | (0.00)       | (0.17)       |
| Weekly ICU (per mill.) (t - 21)  | 0.00         | 0.00         | −0.00        | −0.00        | −0.00        | −0.20        |
|                                  |              |              |              |              |              | (0.19)       |
| Total booster (per hund.) (t - 21)| 0.00         | 0.00         | −0.00        | −0.00        | −0.00        | −0.02        |
|                                  |              |              |              |              |              | (0.04)       |
| Time (No. of days) (t - 21)      | −0.01***     | −0.00        | −0.00        | 0.01***      | −0.01***     | 0.01***      |
|                                  | (0.00)       | (0.00)       | (0.00)       | (0.00)       | (0.00)       | (0.00)       |
| Constant                        | 178.24***    | 62.95        | 77.71        | −178.58***   | 208.27***    | −323.39***   |
|                                  | (36.86)      | (46.48)      | (50.25)      | (40.30)      | (38.89)      | (58.56)      |
| N (# of countries)              | 6913 (46)    | 5177 (45)    | 4605 (40)    | 1539 (19)    | 926 (14)     | 549 (13)     |
| F (5, 45)                       | 20.63***     | 31.93***     | 44.09***     | 51.06***     | 45.60***     | 57.12***     |
| F (6, 44)                       |              |              |              |              |              |              |
| F (7, 39)                       |              |              |              |              |              |              |
| F (8, 18)                       |              |              |              |              |              |              |
| F (9, 13)                       |              |              |              |              |              |              |
| F (10, 12)                      |              |              |              |              |              |              |
| Within R²                       | 0.14         | 0.27         | 0.35         | 0.73         | 0.71         | 0.79         |

All variables except Time are log-transformed. Coefficients are estimated using Driscoll–Kraay standard errors (reported in parentheses).

*p < 0.10.

**p < 0.05.

***p < 0.01.

A significantly small number of countries report information on hospital and ICU admissions and booster vaccinations, resulting in a drastic reduction in sample sizes.

The effect of ‘total death’ (columns (4)–(6) in Table 2) is robust to inclusion of hospital and ICU admissions, and total booster vaccinations in the model, despite significantly smaller sample size. Contrary to expectations, rates of weekly admission to hospital and ICU seem to negatively affect future vaccination. The unexpected result may result from multicollinearity issues in the presence of high correlation between weekly hospitalization, ICU admission rates, and new death rate. However, the qualitative results are not sensitive to the exclusion of any two of these three variables from the list of covariates.9 A plausible explanation for reduced vaccination uptake following increased hospital and ICU admissions is that these admissions were heavily represented by the very population groups that were prioritized for vaccination in most countries (e.g., older age-cohorts and people with co-morbidities). There is evidence that vaccination response decays with time (Poland, 2010). Table 3 tests the sensitivity of the main results for 7-day to 42-day lagged values of the independent variables (except, stringency index and time trend). The results reveal interesting variation in the prevalence and fatality elasticities with temporal lags. It appears that new COVID-19 cases significantly affect vaccination rate for up to a month when the elasticity falls to 0.11. However, both new and cumulative COVID-19 fatality rates begin to influence uptake of vaccination in the longer-term - between 4 and 6 weeks, with one percent increase in new death rate inducing new vaccination rate by 0.08 percent and 0.13 percent, respectively, 4 and 6 weeks later. The effects of total deaths remain intact. The results are robust to the choice of alternative time lags - for example 10-, 20-, 30-, and 40-day lags of the independent variables. Hence, severity of COVID-19, as measured by deaths rates, may be a longer-term driver of vaccine demand in the European countries. All results are also robust to inclusion of a non-linear time trend potentially controlling for any non-monotonic trends in vaccine uptake.

9 The 21-day prior contemporaneous pairwise correlation coefficients are given by: (‘new deaths/million’ & ‘weekly hospital admissions/million’) = 0.85; (‘new deaths/million’ & weekly ICU admissions/million) = 0.81; and (‘weekly hospital admissions/million’ & weekly ICU admissions/million) = 0.92. The sensitivity tests show statistically significant negative effects of hospitalization and ‘booster’ vaccination on future vaccination uptake when new deaths and ICU admission rate are excluded from the regression model. In absence of new deaths and hospital admission rates, the estimated coefficient of ICU admission rate remains negative at 10 percent level of significance. All results are available upon request.
Table A.3
Determinants of new vaccination: Fixed effects estimation at 21-day lag (excluding 19 small countries with population less than 2 million).

| New vaccinations (per mill.) ($t$) | Sensitivity test results |
|----------------------------------|--------------------------|
|                                  | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          |
| New cases (per mill.) ($t - 21$) | 0.26***      | 0.23***      | 0.20***      | 0.72***      | 0.80***      | 0.67***      |
|                                  | (0.05)       | (0.05)       | (0.05)       | (0.06)       | (0.07)       | (0.15)       |
| Total cases (per mill.) ($t - 21$) | 2.02***      | 1.37***      | 0.95***      | 0.69*        | 0.46        | −1.17       |
|                                  | (0.55)       | (0.42)       | (0.42)       | (0.34)       | (0.40)       | (1.40)       |
| New deaths (per mill.) ($t - 21$) | −0.02        | 0.01         | 0.06         | −0.03        | −0.03        | −0.22**      |
|                                  | (0.05)       | (0.05)       | (0.05)       | (0.04)       | (0.06)       | (0.08)       |
| Total deaths (per mill.) ($t - 21$) | 0.73         | 1.36**       | 1.52**       | 3.06***      | 1.63***      | 6.34*        |
|                                  | (0.80)       | (0.57)       | (0.53)       | (0.79)       | (1.12)       | (3.08)       |
| No. fully vaccd. (per hund.) ($t - 21$) | −0.99***     | −0.82***     | −3.17***     | −3.24***     | −3.66***     |             |
|                                  | (0.25)       | (0.24)       | (0.32)       | (0.34)       | (0.45)       |             |
| Stringency index ($t$)           | 0.02***      | 0.00         | 0.00         | 0.00         | 0.00         |             |
|                                  |             |             | (0.00)       | (0.00)       | (0.00)       |             |
| Weekly hosp. (per mill.) ($t - 21$) |              |             |             | −0.57***     | −0.41***     | −0.04        |
|                                  |              |             |             | (0.07)       | (0.11)       | (0.20)       |
| Weekly ICU (per mill.) ($t - 21$) |              |             |             | −0.23*       | −0.23*       | −0.20        |
|                                  |              |             |             | (0.11)       | (0.20)       |             |
| Total booster (per hund.) ($t - 21$) |              |             |             |              | 0.00         |             |
| Time (No. of days)               | −0.01***     | −0.01*       | −0.01*       | 0.01***      | −0.01***     | 0.01***      |
|                                  | (0.00)       | (0.0)        | (0.0)        | (0.00)       | (0.00)       | (0.00)       |
| Constant                         | 231.60**     | 95.15*       | 115.75**     | −177.68***   | 209.73***    | −283.21***   |
|                                  | (38.24)      | (47.17)      | (49.92)      | (39.81)      | (39.16)      | (58.24)      |
| N (# of countries)               | 5600 (32)    | 4278 (32)    | 3982 (31)    | 1631 (15)    | 845 (9)      | 519 (9)      |
| Within R²                         | 0.19         | 0.31         | 0.36         | 0.75         | 0.75         | 0.81         |

Note: The 19 excluded countries are: Andorra, Cyprus, Estonia, Faeroe Islands, Gibraltar, Guernsey, Iceland, Isle of Man, Jersey, Kosovo, Latvia, Liechtenstein, Luxembourg, Malta, Monaco, Montenegro, San Marino, Slovenia, and Vatican. All variables except Time are log-transformed. Coefficients are estimated using Driscoll–Kraay standard errors (reported in parentheses).

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

The sensitivity of the results is tested excluding the United Kingdom (UK) from the sample. Large scale vaccination in the UK began much ahead of the rest of Europe (see Table A.1 in Appendix), mainly due to early authorization and administration of the Astra-Zeneca vaccine, which may have put the country on a higher vaccination trajectory relative to other European countries. The associated time-varying epidemiological factors may not be controlled for in a fixed effects model. However, as shown in column 3 of Table A.2 in Appendix, the results are robust to the exclusion of the UK. Without the UK in the sample, the fatality elasticity increases to 2.18, perhaps reflecting stronger effects of COVID-19 deaths in reducing vaccine complacency in the rest of Europe.

Finally, the results are tested by excluding from the sample the following countries with a population of less than 2 million as of July 02, 2021: Cyprus, Estonia, Latvia, Luxembourg, Malta, Slovenia, Andorra, Iceland, Monaco, Montenegro, San Marino, Faeroe Islands, Guernsey, Gibraltar, Isle of Man, Jersey, Liechtenstein, Kosovo, and Vatican. Some of these small countries have considerably less negotiation and purchasing power, which may have posed unique country-specific challenges for COVID-19 vaccine acquisition and rollout (Palmer et al., 2021). Table A.3 in Appendix shows that the main results remain unaffected by the exclusion of these countries. Column 3 shows that the prevalence elasticity is 0.20, while the fatality elasticity is 1.52.

Although the rollout of vaccines may have been restricted in parts of Europe due to supply and distribution constraints, demand may still have played a role in vaccine uptake. Hence, it may be informative to re-examine the results setting an earlier start date of the sample. The results, presented in Tables A.4 and A.5 in Appendix, show that the results are robust to moving the sample start date by more than two months to April 21. In fact, the qualitative results hold for any start date in between April–July 2021.

10 For more detail, see: https://eurohealthobservatory.who.int/monitors/hsrm/analyses/hsrm/how-has-the-covid-19-vaccination-been-rolled-out-in-small-countries-within-the-european-region.
Table A.4
Determinants of new vaccination: Fixed effects estimation results at 21-day lag (Sample start date: April 21, 2021).

| New vaccinations (per mill.) ($t$) | Sensitivity test results |
|-----------------------------------|--------------------------|
|                                   | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
| New cases (per mill.) ($t-21$)    | 0.13** | 0.15** | 0.12** | 0.50*  | 0.58** | 0.74** |
| New deaths (per mill.) ($t-21$)   | 0.01  | 0.03  | 0.05  | -0.02 | 0.06  | -0.09 |
| Total cases (per mill.) ($t-21$)  | 1.65*** | 1.22*** | 1.36*** | 4.87**  | 5.72*** | 9.06*** |
| No. fully vacc'd. (per hund.) ($t-21$) | -0.01 | 0.06  | -0.64*** | -0.64*** | -1.45*** |
| Stringency index ($t$)            | 0.01*** | 0.01*** | 0.01*** | 0.01  | 0.01  | 0.01  |
| Weekly hosp. (per mill.) ($t-21$) | -0.05*** | -0.12 | -0.00  | 0.00  | 0.00  | 0.00  |
| Weekly ICU (per mill.) ($t-21$)   | -0.49*** | -0.70*** |
| Total booster (per hund.) ($t-21$) | 0.12**  |
| Time (No. of days) ($t-21$)       | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| Constant                          | 120.90*** | 146.34*** | 152.07*** | 54.59*** | 23.55*** | -84.80*** |

N (# of countries) = 44

All variables except Time are log-transformed. Coefficients are estimated using Driscoll–Kraay standard errors (reported in parentheses).

*p < 0.10.
**p < 0.05.
***p < 0.01.

5. Concluding remarks

The paper empirically tests the prevalence dependence hypothesis, which posits that human self-protective behavior, such as demand for vaccination, responds positively to the perceived threat of a disease. The ongoing vaccination programs in Europe against SARS-CoV-2 has presented a unique opportunity to test this hypothesis on a large scale. Using daily COVID-19 tracking and vaccination data for 47 European countries, the paper finds strong evidence of prevalence dependence of vaccination behavior: controlling for other potential time-varying factors and country-specific fixed effects, a one percent increase in COVID-19 infection and mortality rate increases vaccination rate by about 0.18 percent and 1.53 percent after 21 days, respectively, with the effect sizes monotonically declining with time. These results help underscore the two-way feedback channel whereby vaccination behavior responds to observed disease outcomes, which, in turn, are affected by behavior. An understanding of the link is critical for addressing vaccine complacency — a key ingredient of vaccine hesitancy in certain populations.

More broadly, the results have implications for resource allocation toward pandemic management and mitigation efforts. At high levels of prevalence, additional efforts to increase vaccination uptake, such as vaccine incentives, may be unwarranted because demand for vaccines rises endogenously. However, when infection prevalence is low, vaccine demand may be sub-optimally low in absence of policies to promote vaccination. The latter also imply that eradication of COVID-19 will become increasingly difficult through vaccination only, since declining prevalence rate and disease mortality would also diminish private incentives for prevention. This has serious implications for achieving a target vaccination rate and consequently the ability of the economies to reopen effectively.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Table A.5
Determinants of new vaccination: Fixed effects estimation at 7–42-day lags (Sample start date: April 21, 2021).

| New vaccinations (per mill.) | Coeff (t–7) | Coeff (t–14) | Coeff (t–21) | Coeff (t–28) | Coeff (t–35) | Coeff (t–42) |
|-----------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| New cases (per mill.) | 0.16*** | 0.15*** | 0.12*** | 0.09*** | 0.07** | 0.06* |
| Total cases (per mill.) | 1.37*** | 0.88*** | 0.35 | −0.09 | −0.37 | −0.44 |
| New deaths (per mill.) | −0.00 | 0.02 | 0.05 | 0.08** | 0.10*** | 0.10*** |
| Total deaths (per mill.) | 1.15*** | 1.27 | 1.36*** | 1.32*** | 1.28*** | 1.13*** |
| No. fully vaccd. (per hund.) | 0.31*** | 0.20*** | 0.06 | −0.05 | −0.14 | −0.22** |
| Stringency index | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| Time | −0.01*** | −0.01*** | −0.01*** | −0.01*** | −0.00 | −0.00 |
| Constant | 247.14*** | 206.40*** | 152.07*** | 100.86*** | 59.55* | 25.53 |
| N (# of countries) = 44 | N = 6832 | N = 6826 | N = 6823 | N = 6807 | N = 6793 | N = 6788 |
| F (7, 43) | 48.12*** | 34.05*** | 34.05*** | 38.58*** | 45.52*** | 49.87*** |
| (Prob > F) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Within R² | 0.35 | 0.34 | 0.33 | 0.33 | 0.33 | 0.34 |

All variables except Time are log-transformed.
*p < 0.10.
**p < 0.05.
***p < 0.01.
†Denotes corresponding lag (in days) for new cases (per million), new deaths (per million), no. fully vaccd. (per hundred), total cases (per million), and total deaths (per million). Coefficients are estimated using Driscoll–Kraay standard errors (reported in parentheses).

Appendix

See Tables A.1–A.5.

References

Ahituv, A., Hotz, V.J., Philipson, T., 1996. The responsiveness of the demand for condoms to the local prevalence of AIDS. J. Hum. Resour. 31 (4), 869–897.

Anglewicz, P., Clark, S., 2013. The effect of marriage and HIV risks on condom use acceptability in rural Malawi. Soc. Sci. Med. 97, 29–40.

Auld, M., 2006. Estimating behavioral response to the AIDS epidemic. J. Econ. Anal. Policy 5 (1), 1–29.

Bouck, R., Desbordes, R., Latzer, H., 2009. How do epidemics induce behavioral changes? J. Econ. Growth 14 (3), 233–264.

Cascini, F., Pantovic, A., Al-Azlouni, Y., Failla, G., Ricciardi, W., 2021. Attitudes, acceptance and hesitancy among the general population worldwide to receive the COVID-19 vaccines and their contributing factors: A systematic review. EClinicalMedicine 40, 101113.

Dales, L., Kizer, K.W., Pertowski, C., Waterman, S., Woodford, G., 1993. Measles epidemic from failure to immunize. West. J. Med. 159 (4), 455–464.

Driscoll, John, Kraay, Aart, 1998. Consistent covariance matrix estimation with spatially dependent panel data. Rev. Econ. Stat. 80 (4), 549–560.

Geoffard, P.-Y., Philipson, T., 1996. Rational epidemics and their public control. Internat. Econom. Rev. 37 (3), 603–624.

Geoffard, P.-Y., Philipson, T., 1997. Disease eradication: Private versus public vaccination. Amer. Econ. Rev. 87 (1), 222–230.

Hoechle, D., 2007. Robust standard errors for panel regressions with cross-sectional dependence. Stata J. 7 (3), 281–312.

Magadi, M.A., Agwanda, A.O., 2010. Investigating the association between HIV/AIDS and recent fertility patterns in Kenya. Soc. Sci. Med. 71 (2), 335–344.

Manfredi, P., D’Onofrio, A., 2013. Modeling the Interplay Between Human Behavior and the Spread of Infectious Diseases. Springer, New York.

Mullahy, J., 1999. If it’ll only hurt a second? Microeconomic determinants of the demand for flu vaccines. Health Econ.

Philipson, T., 1996. Private vaccination and public health: An empirical examination for U.S. measles. J. Hum. Resour. 31 (3), 611–630.

Philipson, T.J., 2000. Economic epidemiology and infectious diseases. Handb. Health Econ. 1, 1761–1799.

Philipson, T., Posner, R., 1993. Private Choices and Public Health: An Economic Interpretation of the AIDS Epidemic. Harvard University Press, Cambridge, MA.

Poland, G.A., 2010. The 2009–2010 pandemic influenza: effects on the demand and seasonal vaccine uptake and lessons learned for seasonal vaccination campaigns. Vaccine 28, D3–D13.

Sallam, M., 2021. COVID-19 vaccine hesitancy worldwide: A concise systematic review of vaccine acceptance rates. Vaccines 9 (2), 160.

SteelFisher, G.K., Blendon, R.J., Bekheit, M.M., Lubell, K., 2009. The public’s response to the 2009 H1N1 influenza pandemic. N. Engl. J. Med. 362 (22), e65.

Weston, F., Willem, L., Beutels, P., 2016. Behavioral change models for infectious disease transmission: A systematic review (2010–2015). J. R. Soc. Interface 13.

Weston, D., Hauck, K., Amlôt, R., 2018. Infection prevention behaviour and infectious disease modelling: A review of the literature and recommendations for the future. BMC Public Health 18, 336.