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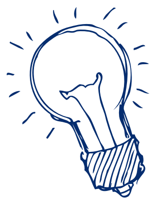

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Causal effects of vaccine uptake and population mobility on COVID-19 cases and deaths in Russia

Ivan Gordeev*

This paper analyzes short-run COVID-19 dynamics in Russia using a weekly panel of 12 regions over 54 weeks. Growth rates of cases and deaths are modeled as functions of vaccination uptake and behavioral activity, with region fixed effects and a set of controls. Identification uses three sources of exogenous variation: the timing of regional QR-code mandates as an instrument for Retail & Recreation mobility, news about potential WHO approval of Sputnik V interacted with the mandate indicator, and a short post-mandate window as instruments for vaccination. First-stage diagnostics show strong relevance (the homoskedastic partial F-statistics are 519 for mobility and 98 for vaccination), while event-study and placebo checks detect no pre-trends or reverse-timing effects (future WHO-related news terms do not predict current vaccination). TSLS estimates indicate a clear protective role of vaccination (particularly full immunization) and a positive causal impact of mobility. The six-week vaccination lag reduces future growth in cases and deaths, with the effect more than twice as large as naïve OLS suggests. The impact of mobility on subsequent cases and deaths is about twice as large as suggested by OLS and remains robust across different specifications. Overall, under standard IV assumptions, completing full vaccination and reducing high-contact leisure activity substantially reduce short-run transmission and mortality.

JEL Classification: I18, I12, C23, C26.

Keywords: COVID-19, vaccination, behavioral response, two-stage least squares, Russia, panel data, instrumental variables.

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1 Introduction

Epidemiological research has received renewed attention in recent years as a result of the COVID-19 pandemic. In 2025, it remains a major public health concern. The demographic literature documents an unusually high and regionally heterogeneous COVID-19 mortality burden in Russia (Timonin et al., 2021; Shkolnikov et al., 2022). Given this context, this paper analyzes the effects of vaccination and population mobility on transmission and mortality across Russia's largest regions using an instrumental variables approach within a panel data framework. In particular, I model epidemic dynamics as a function of vaccination uptake and public behavior, treating both variables as endogenous.

Vaccination dynamics are explained by the growth rate of confirmed cases (an information variable capturing perceived risk), a short-run post-policy window following the introduction of regional QR-code requirements, and news coverage of the potential approval of the Sputnik V vaccine by the World Health Organization interacted with the mandate indicator. The latter two terms serve as excluded instruments in the first stage: the WHO-related news is relevant only once mandates are in place and is context-specific to Russia. Within the country, no WHO-approved alternatives were available, making public discussions about Sputnik V crucial for trust in vaccination. This specification is similar to Karaivanov et al. (2022), with the novel news instrument as the key modification.

Behavioral dynamics are described by the growth rate of confirmed cases (a proxy for perceived risk associated with going out), the QR-code mandate indicator, and a variable capturing behavioral patterns during long holidays. The mandate indicator is the main instrument in the first-stage equation since it is strongly correlated with behavior. This behavioral specification follows Chernozhukov et al. (2021) and Karaivanov et al. (2021), with the addition of the long-holiday control capturing the national holiday calendar. In the Russian context, Egorov et al. (2021) show that ethnic diversity and social heterogeneity shape social distancing (with similar evidence for the United States), while my focus is on epidemiological risk and policy-driven responses.

To capture behavioral dynamics, I use two measures: the intensity of visits to retail and recreation venues (such as restaurants, museums, and shopping malls) and the intensity of public transit use. They have been derived from Google's Community Mobility Reports. According to Gordeev (2025a), both measures serve as the most reliable proxies for overall public activity among the six Google mobility categories because they have consistent correlations with COVID-19 cases and vaccination uptake.

Many studies in epidemiology start with the Susceptible-Infected-Removed (SIR) model by Kermack and McKendrick (1927), which describes epidemic dynamics in a population. However, the basic SIR framework omits behavioral responses, which are essential when outcomes depend on individual decisions. Gans (2022) and Ellison (2024) extend the model as follows: individuals derive utility from activity, but greater activity increases exposure risk for susceptible individuals (those who have not yet been infected). These extensions suggest that activity decreases as the number of infections rises. In other words, the more people are infected, the less active individuals become in order to avoid risky contacts. As mentioned above, I use Retail & Recreation and Transit Stations as proxies for activity.

This paper is organized as follows. Section 2 describes the data, its sources, and cleaning procedures. Section 3 presents the baseline model. Section 4 estimates the first-stage regressions of the endogenous variables on their instruments. Section 5 develops the identification strategy. Section 6 reports results for measures of COVID-19 spread using OLS and TSLS. Section 7 concludes with a summary of findings.

2 Data

This study uses data available at the repository: https://github.com/ivagormih/Covid-in-Russia/blob/96377b11fb1850c460632be1e486b065317e3aa6/covid19_russia.csv. After cleaning, the dataset contains a balanced weekly panel of 12 Russian regions, each observed for 54 weeks (648 region-week observations: $N = 12$, $T = 54$). The sample covers the period from January 1, 2021, through January 14, 2022, before the Omicron variant became dominant in Russia. Because Omicron differs substantially from earlier variants, post-Omicron weeks have been excluded from the sample to avoid a structural break.

Table 1. Main Variables

Notation	Definition	Source
Y_{it}	weekly growth of cumulative cases weekly growth of new cases weekly growth of cumulative deaths	Yandex DataLens
Δv_{it}	weekly new vaccinations (% of population)	GOGOV
RR_{it} TS_{it}	intensity of visits to retail and recreation locations intensity of public transit use	Google Mobility

The main variables used in this study are summarized in Table 1. In particular, if C_{it} denotes the cumulative number of people in the population of region i who have ever tested positive up to week t, then $Y_{it} = \log C_{it} - \log C_{i,t-1}$ is the weekly growth rate of cumulative cases.

The weekly growth of cumulative deaths is defined analogously. As for the growth of new cases, it is $Y_{it} = \log \Delta C_{it} - \log \Delta C_{i,t-1}$, where $\Delta C_{it} = C_{it} - C_{i,t-1}$. Vaccination is introduced based on the information about the first dose of the vaccine, $\Delta v_{it} = v_{it} - v_{i,t-1}$, where $v_{it} = \frac{V_{it}}{N_{it}}$ is the cumulative percentage of vaccinations. The vaccination series from GOGOV contains missing values, so I linearly interpolated the daily figures within each region before aggregating to weekly shares, which were then differenced to obtain Δv_{it}. As for activity variables, they are derived from Google Mobility data and reflect movement trends across different categories of places, calculated as weekly averages relative to a pre-pandemic baseline. Gordeev (2025a) shows that Retail & Recreation and Transit Stations proxy public behavior more reliably than other Google categories.

The dataset contains information on 15 regions of Russia (see Appendix A), but the analysis focuses on 12 because I exclude three regions due to atypical correlation patterns. As documented in Gordeev (2025a), Krasnodar Krai has positive correlations between behavioral variables and confirmed cases because of tourism-driven mobility. Tatarstan has a markedly stronger negative correlation between Transit Stations mobility and cases after introducing region-wide QR-code requirements for public transit in 2021. Finally, Moscow is a large city with distinct policy timing and mobility patterns, so I analyze it separately (Gordeev, 2025b). Accordingly, these three regions have been excluded from the estimation sample.

Apart from the main variables, I introduce instruments for the first stage to address endogeneity in vaccination and behavior. First, I use a policy dummy defined as $p_{it} = 1\{t \geq \tau_i\}$, where τ_i is the week when QR-code requirements were introduced in region i. Thus, p_{it} captures the long-run policy effects. Second, I use $w_{it} = 1\{t \in [\tau_i, \tau_i + 3]\}$, which captures only the short-run shock following the introduction of the policy. The policy adoption dates were collected from official regional announcements and media reports and are included in the dataset.

Regarding the Sputnik V vaccine, it has never been approved by the World Health Organization. However, the news coverage of the approval process appears to have influenced people's vaccination decisions. Therefore, I introduce S_t, a variable reflecting the tone of international news. It was constructed manually by tracking major news reports and assigning scores for each day based on the perceived direction and relevance of the information (positive, negative, or neutral). The S_t series is not included in the initial dataset but available at: https://github.com/ivagormih/Covid-in-Russia/blob/a61145e5a6055ad610e1ec69d26db97a0069a048/sputnik.csv. For this research, I use $s_t = S_t - \bar{S}$ (where $\bar{S}$ denotes the sample mean) in order to improve interpretability. By construction, s_t varies over time but not across regions.

3 Baseline Model

This section formally specifies the baseline model of the study and explains why OLS estimates may fail to capture the true effects of vaccine uptake and population mobility. The starting point is the following panel equation:

$$Y_{i,t+l} = \beta_1 \Delta v_{i,t-3} + \beta_2 \Delta v_{i,t-6} + \beta_3 RR_{it} + X'_{it}\gamma + \alpha_i + \varepsilon_{i,t+l}, \tag{1}$$

where the dependent variable Y_{it} measures COVID-19 incidence dynamics. Specifically, I use the weekly growth rate of cases, defined as $Y_{it} = \log C_{it} - \log C_{i,t-1}$, with C_{it} denoting the cumulative number of confirmed cases in region i. The three-week and six-week lags of new weekly vaccinations are intended to capture the effects of the first and second vaccine doses, respectively. The variable RR_{it} is a behavioral measure of the intensity of visits to Retail & Recreation places. I set $l = 1$ when the outcome is COVID-19 cases, which accounts for the incubation period (see Wu et al., 2022, for evidence on incubation periods) and the time needed to obtain PCR test results. X_{it} is a vector of control variables defined in the next section.

For robustness, I also consider alternative outcome variables. First, following Chernozhukov et al. (2021), I analyze not only growth rates but also the acceleration of cases, defined as $Y_{it} = \log \Delta C_{it} - \log \Delta C_{i,t-1}$, where $\Delta C_{it} = C_{it} - C_{i,t-1}$. Second, I use the weekly growth rate of deaths, defined analogously as $Y_{it} = \log D_{it} - \log D_{i,t-1}$. When the outcome is deaths, I set $l = 3$, reflecting approximately one week from infection to case detection and two weeks from case detection to death (Linton et al., 2020). To account for serial correlation in mortality, I also include a one-week lag of the dependent variable as an additional regressor.

The major problem arises from the fact that growth in current cases has a positive effect on vaccination and a negative effect on Retail & Recreation mobility. In particular, when the public observes that the virus becomes more prevalent, they tend to reduce their visits to entertainment venues, such as restaurants or theaters. Meanwhile, they get more incentives to get vaccinated for additional protection. This creates simultaneity and endogeneity.

This paper addresses the problem by treating Δv_{it} and RR_{it} as endogenous. They are instrumented using policy-related shocks and the news about the potential approval of Sputnik V vaccine by the World Health Organization. I document strong relevance (partial F-statistics) for both vaccination and mobility. In addition, the instruments are plausibly exogenous with respect to cases and deaths, affecting them only through the endogenous variables. The next section introduces the first stage of the two-stage least squares approach and presents the empirical results.

4 First Stage

In this section, I formally define behavioral activity and vaccination, specifying their dynamic evolution and key determinants. Furthermore, these variables are identified as the primary sources of endogeneity in the empirical model. Individual activity is measured using two distinct mobility indicators: Retail & Recreation, capturing visits to restaurants, shopping malls, and cultural venues; Transit Stations, measuring the intensity of public transport use. RR_{it} is the main measure for region $i = 1, \ldots, N$ and week $t = 1, \ldots, T$, while TS_{it} is included only for comparison. Higher values of RR_{it} indicate greater out-of-home activity. The first-stage regression for mobility is

$$RR_{it} = \beta_1 p_{it} + \beta_2 h_t + \beta_3 \Delta \log C_{it} + \beta_4 M_t + \gamma t + \alpha_i + \varepsilon_{it}. \quad (2)$$

Here, α_i are region fixed effects, $\Delta \log C_{it} = \log C_{it} - \log C_{i,t-1}$ is the weekly growth rate of cumulative cases, p_{it} is a policy indicator, h_t captures long federal holidays in 2021, M_t is an indicator for the mass vaccination campaign in Moscow, and t is a linear time trend.

As for h_t, it reflects the holiday schedule. In particular, New Year's Day is one of the most celebrated holidays in Russia and typically leads to increased activity. Thus, h_t is positive for two weeks before December 31 and negative for two weeks after it (with values of 0.5, 1, -1, and -0.5, respectively). Moreover, the index captures holidays in May and non-working days in November: the two weeks from April 30 to May 14 take the value -1 due to strong recommendations to stay home, and the two weeks from October 29 to November 12 likewise take the value -1.

The variable M_t is defined as $M_t = 1\{t \in [\tau_M, \tau_M + 7]\}$, where τ_M is the week immediately preceding the introduction of QR-code requirements in Moscow. The capital's policy created a short-run nationwide push for vaccination, so I include a control for this eight-week window. Although a direct effect on Retail & Recreation mobility is unlikely, I include M_t in equation (2) to keep the set of exogenous controls identical across all first-stage regressions, consistent with the standard TSLS approach.

Modeling vaccination dynamics is more complex than modeling behavior, but I follow Karaivanov et al. (2022), who explain vaccination using growth of cases as an information variable and policy interventions adopted by the government. In addition, I include a Russia-specific instrument for vaccination uptake: news coverage of the potential WHO approval of Sputnik V. The first-stage regression for vaccine uptake is

$$\Delta v_{it} = \beta_1 s_t p_{it} + \beta_2 w_{it} + \beta_3 \Delta \log C_{it} + \beta_4 M_t + \beta_5 h_t + \gamma t + \alpha_i + \varepsilon_{it}. \quad (3)$$

The dependent variable Δv_{it} denotes new weekly first-dose vaccinations (% of population). The WHO-news index s_t has a significant influence on people's decisions only after the policy introduction (see Appendix B), so it enters equation (3) interacted with p_{it}. The short-run policy window w_{it} takes the value 1 in the four weeks following τ_i (the week when QR-code requirements were introduced in region i). The Moscow-specific dummy M_t captures the nationwide push induced by the capital's policy. Holidays h_t are included as a calendar control to absorb seasonality (such as clinic schedules).

In order to avoid potential omitted variable bias, equation (3) should include not only the interaction term $s_t p_{it}$ but also both main effects. However, adding p_{it} and s_t as separate regressors in the first-stage vaccination equation would alter the identification strategy. Either they become additional excluded instruments for vaccination (which risks violating the exclusion restriction), or they must also enter the second stage as controls. In the latter case, p_{it} can no longer serve as the excluded instrument for Retail & Recreation mobility. Therefore, equation (3) includes only the interaction $s_t p_{it}$. As a robustness check (Appendix C), I include the interaction together with both main effects, treating Retail & Recreation mobility as exogenous. The vaccination results are qualitatively similar to those presented in Section 6, while the mobility coefficient is indistinguishable from zero and should not be interpreted as causal because it is not instrumented.

Table 2. First Stage Estimation

Dependent variable: RR_{it}		Dependent variable: $100 \times \Delta v_{it}$	
p_{it}	-13.87^{***} (0.65)	$s_t \times p_{it}$	0.38^{***} (0.08)
–	–	w_{it}	1.07^{***} (0.15)
$\Delta \log C_{it}$	-264.43^{***} (18.90)	$\Delta \log C_{it}$	0.32 (1.88)
M_t	-0.52 (0.34)	M_t	0.79^{***} (0.06)
h_t	8.77^{***} (0.73)	h_t	0.12 (0.07)
t	0.39^{***} (0.01)	t	0.02^{***} (0.002)
α_i (region FE)	Yes	α_i (region FE)	Yes
Partial F (homosk.)	519.14	Partial F (homosk.)	98.22
Observations	$N \times T = 636$	Observations	$N \times T = 635$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors in parentheses are heteroskedasticity-robust (HC1).

Table 2 reports the first-stage estimates. It is worth noting that the vaccination variable is scaled by 100 to improve readability. In equation (2), the excluded instrument is the policy indicator p_{it}, while in equation (3) the excluded instruments are the WHO-news after the policy introduction $s_t p_{it}$ and the four-week post-introduction window w_{it}. All specifications include the same set of exogenous controls: $\Delta \log C_{it}$, the Moscow campaign dummy M_t, the holiday index h_t, a linear time trend *t*, and region fixed effects α_i. The homoskedastic partial F-statistics are 519 for RR_{it} and 98 for Δv_{it}, above the conventional threshold of 10 (Stock and Yogo, 2005), indicating strong instrument relevance.

The policy indicator is associated with lower Retail & Recreation mobility, consistent with restrictions on visits to shopping malls, cafés, and other venues. Vaccinations increase with WHO-related news, but only once the policy is in place, and they also rise within the short post-policy window w_{it}. Holidays raise mobility, while the Moscow campaign dummy is positively related to vaccination – these controls were specifically designed for their corresponding endogenous variables. As expected, the coefficient for $\Delta \log C_{it}$ is strongly negative in the mobility equation (activity falls when cases rise) and statistically insignificant in the vaccination equation.

5 Identification

In the previous section, I use the policy indicator $p_{it} = 1\{t \geq \tau_i\}$ for QR-code requirements as an instrument for Retail & Recreation mobility. As shown in Table 2, it is highly relevant since the estimate is negative (about -14 with p < 0.001) and the homoskedastic partial F-statistic for the excluded instrument in the RR_{it} first-stage regression is 519, which is far above the conventional threshold of 10 (Stock and Yogo, 2005). An event study around τ_i (Appendix D) detects no pre-trends, as the pre-policy indicators $p_{i,t-4}$, $p_{i,t-3}$, $p_{i,t-2}$ are individually insignificant, as well as jointly (p = 0.23), when using region-clustered standard errors. The indicator $p_{i,t-1}$ is omitted as the reference period. Post-policy indicators are significant, with the largest responses for $p_{i,t+1}$ and $p_{i,t+4}$. The absence of effects for $p_{i,t+2}$ and $p_{i,t+3}$ (joint p = 0.26) is consistent with stepwise local policy implementation (for example, shopping malls first, restaurants later), which can plausibly lead to a second decline in activity by week 4.

Turning to the instruments for vaccination, I use two excluded predictors in the first stage for Δv_{it}: the WHO-related news after the policy introduction, $s_t p_{it}$, and the short-run post-introduction window w_{it} (which equals 1 in the four weeks following τ_i). Both are relevant in the first-stage equation for vaccination (Table 2 reports a homoskedastic partial F-statistic of 98 for the set of excluded instruments). Placebo checks in Appendices E and F support their exclusion restrictions. The variable $s_t p_{it}$ captures global information shocks about potential WHO approval of Sputnik V that matter only once local mandates are in place. Such news plausibly shifts perceived vaccine quality and acceptance but has no direct biological effect on infection dynamics. Similarly, the four-week window w_{it} (which equals 1 for weeks $t \in [\tau_i, \tau_i + 3]$) reflects short-run implementation intensity that increases vaccine uptake but has no direct effect on infections if behavior and cases are controlled for.

First, the future values of the WHO-news instrument $s_{t+k} p_{i,t+k}$ for $k \in \{1, 2, 3\}$ do not predict current vaccinations (see Appendix E). The estimates are tiny and jointly insignificant (Wald test yields joint p = 0.39). Second, for the short-run window w_{it}, an event study with one-week pre-policy dummies $f_{i,t-k} = 1\{t = \tau_i - k\}$ for $k \in \{1, 2, 3\}$ detects no pre-trend (see Appendix F). All coefficients are small and jointly insignificant (Wald test yields joint p = 0.20), while w_{it} itself remains positive and significant.

A key identification concern is reverse causality: surges in new cases could both stimulate policy and directly lower mobility. I mitigate this by controlling for $\Delta \log C_{it}$, region fixed effects α_i, and a common trend t. Therefore, these tests suggest that vaccination is not predicted by past values of policy, and there are no reverse-timing effects (future news does not influence the current uptake), which supports the exclusion restrictions for $s_t p_{it}$ and w_{it}. All specifications use the same set of exogenous controls: $\Delta \log C_{it}$, the Moscow campaign dummy M_t, the holiday index h_t, a linear trend t, and region fixed effects α_i. Combined with the strong instruments, this evidence forms the basis of the identification strategy.

6 Main Model

In this section, I estimate the second-stage regression and discuss the results in detail. First, I apply OLS as a baseline model. Then, I implement two-stage least squares (TSLS), using the excluded instruments described in the previous section to address endogeneity.

Virus transmission is modeled as a function of behavioral activity, new weekly vaccinations, and a set of control variables:

$$\Delta \log C_{i,t+1} = \beta_1 \Delta v_{i,t-3} + \beta_2 \Delta v_{i,t-6} + \beta_3 RR_{it} + X'_{it}\gamma + \alpha_i + \varepsilon_{i,t+1}, \tag{4}$$

where $\beta_1, \beta_2, \beta_3$ are the coefficients to be estimated. The three-week and six-week lags of vaccine uptake are intended to capture the effect of the first and second doses, respectively. The one-week lag of cases aggregates the incubation period (see Wu et al. (2022) for evidence on incubation periods) and the time to receive PCR test results. The controls set X_{it} contains M_t and h_t (special week indicators), a common time trend t, and $Y_{it} = \Delta \log C_{it}$. I report OLS estimates for equation (4) and then compare them with TSLS.

Table 3. Estimation of Cases

	Dependent variable: $100 \times \Delta \log C_{i,t+1}$		
	OLS		TSLS
$\Delta v_{i,t-3}$	-9.93^{***} (3.14)	-11.62^{***} (2.94)	-14.09^{***} (3.46)
$\Delta v_{i,t-6}$	-12.92^{***} (2.13)	-11.14^{***} (1.97)	-32.47^{***} (3.38)
RR_{it}	0.02^{***} (0.002)	–	0.04^{***} (0.004)
TS_{it}	–	0.01^{***} (0.001)	–
$\Delta \log C_{it}$	96.97^{***} (2.78)	96.09^{***} (2.68)	104.34^{***} (2.50)
M_t	0.25^{***} (0.04)	0.24^{***} (0.04)	0.16^{***} (0.04)
h_t	-0.23^{***} (0.04)	-0.22^{***} (0.04)	-0.40^{***} (0.04)
t	0.007^{***} (0.002)	0.008^{***} (0.001)	0.01^{***} (0.002)
α_i (region FE)	Yes	Yes	Yes
Partial F (homosk.)	–	–	RR_{it}: 519.14 Δv_{it}: 98.22
Observations	$N \times T = 563$	$N \times T = 563$	$N \times T = 550$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors in parentheses are heteroskedasticity-robust (HC1).

Estimation results for future case growth are reported in Table 3. The dependent variable is $\Delta \log C_{i,t+1}$ scaled by 100. Columns 1 and 2 estimate the model using OLS for Retail & Recreation and Transit Stations as the activity measure. Column 3 reports the TSLS specification in which RR_{it}, $\Delta v_{i,t-3}$, and $\Delta v_{i,t-6}$ are treated as endogenous. All specifications include region fixed effects, the current case growth $\Delta \log C_{it}$, special-week dummies (M_t and h_t), and a linear time trend t. Standard errors are heteroskedasticity-robust (HC1).

Across the two OLS columns, both vaccination lags are negative and highly significant: the three-week lag ranges from -11.6 to -9.9 and the six-week lag lies between -12.9 to -11.1. In the TSLS column, the six-week effect becomes substantially larger (approximately -32.5), while the effect of the three-week increases slightly to -14.1. This pattern is consistent with protection building over time, as instrumental variables correct attenuation and simultaneity bias. Activity is positively associated with next-week cases: this effect rises from nearly 0.01-0.02 in OLS to approximately 0.04 in TSLS, again consistent with OLS attenuation (for example, measurement error or negative simultaneity). The epidemic exhibits strong persistence: the coefficient on $\Delta \log C_{it}$ is near 1 in OLS (0.96-0.97 when rescaled back) and slightly above in TSLS (about 1.04). The linear time trend is significant and does not change dramatically across specifications. These TSLS patterns are consistent with concerns about downward bias in naïve OLS estimates: using instruments tends to strengthen estimated vaccination effects when endogeneity and measurement error are mitigated (Hansen and Mano, 2023).

The strength of all instruments is high. The homoskedastic partial F-statistics from the first stage are 519 for RR_{it} and 98 for Δv_{it}, which is well above conventional thresholds (Stock and Yogo, 2005). Overall, the TSLS results reinforce a meaningful protective effect of vaccination (particularly at six weeks) and a positive causal impact of mobility on subsequent cases.

Following Chernozhukov et al. (2021), I use the acceleration of cases by re-estimating equation (1) with Y_{it} defined as $\Delta \log \Delta C_{it} = \log \Delta C_{it} - \log \Delta C_{i,t-1}$. Appendix G shows that the findings for RR_{it} are similar to the main specification: the estimate increases from 0.67-0.81 under OLS to 1.71 under TSLS. For vaccination, the pattern differs: while the six-week lag rises roughly threefold, from -513 to -1592, the three-week lag weakens from -340 to -229.

Similarly, I model the equation for future deaths as a function of behavioral activity, new weekly vaccinations, and the same set of controls:

$$\Delta \log D_{i,t+3} = \beta_1 \Delta v_{i,t-3} + \beta_2 \Delta v_{i,t-6} + \beta_3 RR_{it} + \delta \Delta \log D_{i,t+2} + X_{it}' \gamma + \alpha_i + \varepsilon_{i,t+3}. \qquad (5)$$

I forecast growth of deaths three weeks ahead to align with epidemiological timing: deaths typically occur about two weeks after case detection, with case detection itself occurring roughly one week after infection (Linton et al., 2020). I include a one-week lag of the dependent variable as an additional regressor ($\Delta \log D_{i,t+2}$) to account for serial correlation. Table 4 reports estimates for equation (5), where the outcome is scaled by 100 to improve readability. Columns 1 and 2 present OLS results with Retail & Recreation and Transit Stations as alternative activity measures, while column 3 reports the TSLS specification in which RR_{it}, $\Delta v_{i,t-3}$, and $\Delta v_{i,t-6}$ are treated as endogenous and instrumented as described above.

Table 4. Estimation of Deaths

	Dependent variable: $100 \times \Delta \log D_{i,t+3}$		
	OLS		TSLS
$\Delta v_{i,t-3}$	-0.18 (3.88)	-1.22 (3.71)	4.89 (7.64)
$\Delta v_{i,t-6}$	-11.24^{***} (3.98)	-9.84^{***} (3.82)	-25.26^{***} (7.84)
RR_{it}	0.02^{***} (0.01)	–	0.04^{***} (0.01)
TS_{it}	–	0.01^{**} (0.005)	–
$\Delta \log D_{i,t+2}$	86.38^{***} (4.21)	86.84^{***} (4.22)	84.35^{***} (4.26)
$\Delta \log C_{it}$	8.09^{*} (4.28)	6.87^{*} (4.09)	16.56^{**} (4.31)
M_t	0.13^{*} (0.08)	0.12^{*} (0.08)	0.03 (0.08)
h_t	-0.06 (0.08)	-0.02 (0.08)	-0.31^{***} (0.10)
t	-0.002 (0.003)	-0.002 (0.003)	-0.004 (0.004)
α_i (region FE)	Yes	Yes	Yes
Partial F (homosk.)	–	–	RR_{it}: 519.14 Δv_{it}: 98.22
Observations	$N \times T = 527$	$N \times T = 527$	$N \times T = 527$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors in parentheses are heteroskedasticity-robust (HC1).

Mortality is highly persistent: the coefficient for $\Delta \log D_{i,t+2}$ is approximately 84-87 with $p < 0.001$ across columns (or 0.84-0.87 without scaling). The six-week lag (a proxy for the effect of full immunization) is negative and significant in all columns (around -11 in OLS and -25 in TSLS), while the three-week lag is small and statistically indistinguishable from zero. This pattern is consistent with clinical evidence that protection against severe outcomes strengthens after completion of full immunization (Andrews et al., 2022; Rahmani et al., 2022).

Activity follows the same pattern as in the results for cases. In particular, Retail & Recreation mobility is associated with an increase in future deaths: the estimate is 0.02 in OLS and 0.04 in TSLS. The larger TSLS coefficients relative to OLS are consistent with attenuation and simultaneity bias in the naïve regressions. The Transit Stations index is also positive and statistically significant in OLS (about 0.01). The growth rate of cases becomes more significant once endogeneity in behavior and vaccination is addressed. The linear time trend is insignificant across specifications, indicating that key time-varying factors are already captured. Taken together, the TSLS results suggest a meaningful protective effect of vaccination on mortality concentrated at the six-week horizon and a positive causal effect from mobility to subsequent deaths.

7 Conclusion

The analysis reveals that population mobility and vaccine uptake are the key drivers of short-run COVID-19 dynamics and that reliable instruments are crucial for isolating their causal effects. The identification strategy uses three sources of exogenous variation: the timing of regional QR-code requirements p_{it} as an instrument for Retail & Recreation mobility, WHO-related news after the introduction of the mandates $s_t p_{it}$ and a four-week post-policy window w_{it} as instruments for weekly vaccination. First-stage diagnostics indicate strong relevance (homoskedastic partial F-statistic is nearly 519 for mobility and about 98 for vaccination). Moreover, event-study and placebo tests find no anticipatory patterns: pre-policy indicators for the mandate are jointly insignificant, future WHO-news terms do not predict current vaccination, and pre-policy one-week dummies for w_{it} are jointly indistinguishable from zero. Together with economic arguments for exclusion (policy timing based on epidemiological guidance and WHO coverage shifting perceptions rather than biology), these results support the validity of the instruments.

As for cases, the TSLS estimates show a clear protective role of vaccination and a positive causal impact of mobility on subsequent infections. The six-week vaccination lag (interpreted as the effect of full immunization) reduces next-week case growth (about -32, compared with -13 under OLS), while the three-week lag is smaller but highly significant (about -14, compared with -10 under OLS). The activity effect rises when moving from OLS to TSLS (from roughly 0.01-0.02 to approximately 0.04), consistent with attenuation and simultaneity in naïve regressions. The dynamics of cases are highly persistent (the coefficient on $\Delta \log C_{it}$ is almost 1 in OLS and slightly above in TSLS).

As for deaths, mortality is strongly persistent (the one-period lag relative to the $t+3$ period is between 0.84 and 0.87). The vaccination pattern differs from the results for cases: the six-week lag is negative and highly significant in TSLS (about -25, compared with -11 in OLS), while the three-week lag remains small and statistically insignificant. Retail & Recreation mobility is positively associated with future death growth and the estimate increases in TSLS relative to OLS (from nearly 0.02 to about 0.04). The current growth rate of cases becomes a significant predictor of deaths at $t+3$ once behavior and vaccination are instrumented.

The evidence implies that accelerating vaccination, especially completing the full vaccination schedule, produces substantial reductions in both infections and mortality in the short run, and that limiting high-contact entertainment activity mitigates transmission and deaths. These findings are robust across alternative activity proxies (Retail & Recreation, Transit Stations) and different outcome variables, and they satisfy placebo and event-study checks. Although no exclusion restriction can be formally proven, the combination of strong first stages, absence of pre-trends, and economic arguments make a compelling case that the estimated effects are causal.

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Appendices

Appendix A. Federal Subjects of Russia

Code	Name	Capital
2	Bashkortostan	Ufa
16	Tatarstan	Kazan
23	Krasnodar Krai	Krasnodar
24	Krasnoyarsk Krai	Krasnoyarsk
36	Voronezh Oblast	Voronezh
52	Nizhny Novgorod Oblast	Nizhny Novgorod
54	Novosibirsk Oblast	Novosibirsk
55	Omsk Oblast	Omsk
59	Perm Krai	Perm
61	Rostov Oblast	Rostov-on-Don
63	Samara Oblast	Samara
66	Sverdlovsk Oblast	Yekaterinburg
74	Chelyabinsk Oblast	Chelyabinsk
77	Moscow	
78	Saint Petersburg	

The table lists codes for the Russian Federation's federal subjects and their administrative centers. Moscow and Saint Petersburg are federal cities, meaning that they function as separate regions.

Appendix B. WHO News Before Mandates

Dependent variable: $100 \times \Delta v_{it}$			
$s_t \times p_{it}$	0.38^{***} (0.08)	w_{it}	1.07^{***} (0.15)
$\Delta \log C_{it}$	0.46 (1.90)	$s_t \times (1 - p_{it})$	-0.01 (0.02)
M_t	0.79^{***} (0.06)	Pre-mandate WHO news = 0 (Wald): $F(1{,}616) = 0.28, p = 0.60$	
h_t	0.12 (0.07)		
t	0.02^{***} (0.002)		
α_i (region FE)	Yes	Observations	$N \times T = 635$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are heteroskedasticity-robust (HC1). The variable $s_t \times (1 - p_{it})$ captures the influence of WHO-related news on vaccination decisions before the introduction of mandates, and it is statistically indistinguishable from zero.

Appendix C. TSLS with Exogenous RR

First Stage Dependent variable: $100 \times \Delta v_{it}$		Second Stage Dependent variable: $100 \times \Delta \log C_{i,t+1}$		
			OLS	TSLS
$s_t \times p_{it}$	0.35^{***} (0.09)	$\Delta v_{i,t-3}$	-4.81^{*} (2.69)	-12.94^{***} (3.57)
w_{it}	1.13^{***} (0.16)	$\Delta v_{i,t-6}$	-14.52^{***} (2.05)	-35.14^{***} (3.45)
s_t	-0.01 (0.02)	s_t	-0.04^{***} (0.01)	-0.05^{***} (0.01)
p_{it}	-0.09 (0.13)	p_{it}	-0.52^{***} (0.08)	-0.55^{***} (0.08)
$\Delta \log C_{it}$	0.51 (1.92)	$\Delta \log C_{it}$	92.62^{***} (2.93)	94.29^{***} (3.10)
M_t	0.77^{***} (0.07)	M_t	0.13^{***} (0.04)	0.12^{***} (0.04)
h_t	0.12^{*} (0.07)	h_t	-0.08^{*} (0.04)	-0.05 (0.04)
t	0.02^{***} (0.003)	t	0.02^{***} (0.002)	0.03^{***} (0.003)
α_i (region FE)	Yes	α_i (region FE)	Yes	Yes
Partial F (homosk.)	94.81	RR_{it}	-0.001 (0.004)	0.000 (0.003)
Observations	$N \times T = 635$	Observations	$N \times T = 563$	$N \times T = 550$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are heteroskedasticity-robust (HC1). The homoskedastic first-stage partial F-statistic for the excluded instruments $s_t \times p_{it}$ and w_{it} is 94.81 (exceeds the conventional threshold of 10), indicating strong relevance. The Wald test of the joint null ($s_t = 0, p_{it} = 0$) in the first stage yields F=0.40, p=0.67. In this robustness, only vaccination is instrumented, while RR_{it} is treated as exogenous, which leads to tiny coefficients.

Appendix D. Event Study for Policy

Dependent variable: RR_{it}			
p_{it}	-5.67^{***} (2.05)	$p_{i,t-4}$	-0.76 (1.61)
$\Delta \log C_{it}$	-298.19^{***} (44.67)	$p_{i,t-3}$	-0.80 (1.37)
M_t	-1.30^{*} (0.71)	$p_{i,t-2}$	-0.91 (1.61)
h_t	5.21^{***} (0.90)	$p_{i,t+1}$	-3.89^{**} (1.52)
t	0.47^{***} (0.02)	$p_{i,t+2}$	0.79 (1.85)
α_i (region FE)	Yes	$p_{i,t+3}$	0.08 (1.61)
Pre-policy (-2, -3, -4) jointly zero: $F(3,11) = 1.70, p = 0.23$		$p_{i,t+4}$	-4.75^{***} (1.35)
Post-policy (+1, +2, +3, +4) jointly zero: $F(4,11) = 23.71, p < 0.01$			
Mid-window (+2, +3) jointly zero: $F(2,11) = 1.53, p = 0.26$		Observations	$N \times T = 552$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are cluster-robust (by region). The indicator $p_{i,t-1}$ is omitted as the reference period.

Appendix E. Placebo test for the WHO news instrument

Dependent variable: $100 \times \Delta v_{it}$			
w_{it}	0.99^{***} (0.16)	$s_{t+1} \times p_{i,t+1}$	0.0002 (0.09)
$\Delta \log C_{it}$	-1.34 (1.70)	$s_{t+2} \times p_{i,t+2}$	0.03 (0.10)
M_t	0.76^{***} (0.07)	$s_{t+3} \times p_{i,t+3}$	0.14 (0.09)
h_t	-0.03 (0.09)	Post-policy (+1, +2, +3) jointly zero (Wald): $F(3,579) = 1.00, p = 0.39$	
t	0.02^{***} (0.002)		
α_i (region FE)	Yes	Observations	$N \times T = 599$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are heteroskedasticity-robust (HC1).

Appendix F. No pre-trend in short-run policy window

Dependent variable: $100 \times \Delta v_{it}$			
$s_t \times p_{it}$	0.35^{***} (0.06)	w_{it}	1.20^{***} (0.30)
$\Delta \log C_{it}$	3.40 (2.68)	$f_{i,t-1}$	0.01 (0.49)
M_t	0.76^{***} (0.13)	$f_{i,t-2}$	0.06 (0.26)
h_t	0.10 (0.08)	$f_{i,t-3}$	0.48^{*} (0.26)
t	0.02^{***} (0.002)	Pre-policy (-1, -2, -3) jointly zero (Wald): $F(3,11) = 1.83, p = 0.20$	
α_i (region FE)	Yes	Observations	$N \times T = 611$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are cluster-robust (by region). $f_{i,t-k}$ are one-week dummies, specifically $f_{i,t-k} = 1\{t = \tau_i - k\}$, where τ_i denotes the week when policies in region i were introduced.

Appendix G. Estimation of Cases (Acceleration)

	Dependent variable: $100 \times \Delta \log \Delta C_{i,t+1}$		
	OLS		TSLS
$\Delta v_{i,t-3}$	-340.09^{***} (128.46)	-420.66^{***} (117.25)	-229.47^{*} (135.72)
$\Delta v_{i,t-6}$	-513.87^{***} (106.49)	-429.24^{***} (99.32)	-1591.66^{***} (181.86)
RR_{it}	0.81^{***} (0.10)	–	1.71^{***} (0.15)
TS_{it}	–	0.67^{***} (0.08)	–
$\Delta \log C_{it}$	-112.51 (92.71)	77.47 (88.74)	354.91^{***} (91.85)
M_t	9.02^{***} (1.45)	8.47^{***} (1.39)	4.77^{***} (1.48)
h_t	-12.77^{***} (2.45)	-12.68^{***} (2.30)	-18.86^{***} (2.32)
t	0.19^{**} (0.08)	0.22^{***} (0.07)	0.37^{***} (0.08)
α_i (region FE)	Yes	Yes	Yes
Partial F (homosk.)	–	–	RR_{it}: 519.14 Δv_{it}: 98.22
Observations	$N \times T = 563$	$N \times T = 563$	$N \times T = 550$

N denotes the number of regions, T denotes the number of weeks. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are heteroskedasticity-robust (HC1).

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