Population and Economics

Population and Economics 7(2): 1–22
DOI 10.3897/popecon.7.e90445

RESEARCH ARTICLE

The effect of the removal of regional anti-COVID restrictive measures on the dynamics of applications for unemployment benefits in Russia

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Received 16 July 2022 ♦ **Accepted** 23 April 2023 ♦ **Published** 27 June 2023

Citation: Suchkova OV, Stavniychuk AY, Kalashnov GY, Osavolyuk AA (2023) The effect of the removal of regional anti-COVID restrictive measures on the dynamics of applications for unemployment benefits in Russia. Population and Economics 7(2):1-22. https://doi.org/10.3897/popecon.7.e90445

Abstract

This paper assesses changes in the dynamics of applications for unemployment benefits in response to the abolition of regional restrictive measures during the first wave of COVID-19 spread in Russia. This assessment is interesting from the perspective of developing anti-crisis support measures for the population. The assessment is based on weekly-regional panel data using the staggered difference-in-differences method. After the lifting of restrictive measures, the number of new applications for unemployment benefits does not decrease significantly. The result remains robust when an alternative measure of the stringency of restrictions is used, such as an indicator for the validity period of digital passes instead of data on the stages of lifting restrictions. A comparison of official data on the effect of restrictive measures with the Yandex self-isolation index is provided.

Keywords

COVID-19, applications for unemployment benefits, restrictive measures, labor market, self-isolation index

JEL codes: C23, E65, J21

Introduction

Unemployment is a standard indicator of economic decline, and monetary authorities take action to counteract its growth (Coibion et al. 2020). According to the study by Kartseva and Kuznetsova (2020), in 2020, one in two Russian employees was engaged in vulnerable employment.

Foreign studies (Baek et al. 2021; Gupta et al. 2020) provide assessments of the short-term effects of restrictive policies in different regions on the dynamics of applications for unemployment benefits in 2020. In Russia, after the implementation of restrictions, there was an increase in benefits and a simplification of the application procedure, which may have contributed to a surge in applications for unemployment benefits. However, due to the simultaneous occurrence of several events, it is not possible to directly confirm or deny this. Instead, this study suggests indirect verification, assuming a symmetric reaction to the implementation and removal of restrictive measures. The study aims to estimate the effect of lifting restrictive measures on the number of approved applications for unemployment benefits. If the increase in benefits is one of the reasons for the surge in applications, then, holding other factors constant, the cancellation of anti-COVID restrictions should not have a significant effect on the emergence of new applications by the unemployed. Additionally, the study examines the potential heterogeneity of this effect by industry.

Methodologically, this study is distinct in that it considers the cancellation of restrictions at different times in different regions, unlike situations where a group of regions cancels anti-COVID restrictions simultaneously. In our case, using standard measures such as differences-in-differences or the Two-Way Fixed Effects (TWFE) model would be inappropriate, as the resulting average would take into account the effect for several regions during certain time periods, which could complicate interpretation (de Chaisemartin and d'Haultfoeuille 2020; Roth et al., in press). Instead, we employ the staggered difference-in-differences method. The results are robust among several specifications and alternative indicators of the restrictive measures effects.

Restrictive measures and measures to support the population in Russia during the COVID-19 pandemic

The outbreak of COVID-19 caused significant perturbation in Russia, leading regional authorities to implement various restrictive measures to curb the virus spread. The initial restrictions were introduced in March 2020. For instance, from March 28 to April 5, public catering establishments (cafés, restaurants), shopping centers, cinemas, and other crowded places were closed (Interfax 2020d). Non-working days were also declared nationwide (Interfax 2020c), and a home self-isolation regime was implemented in Moscow (Interfax 2020a) and other regions (Interfax 2020b). The self-isolation regime was later extended until May 11. Vacationers were prohibited from staying in hotels, sanatoriums, health camps, and other resort areas until June 1. Strict measures were implemented in Moscow and Moscow Oblast, including the closure of shops, beauty salons, and other service sector organizations, in addition to restaurants and cafés (Interfax 2020d). Recommendations were also issued to temporarily suspend concerts, matches, and various exhibitions.

The Russian economy faced significant challenges, prompting the authorities to gradually implement measures to support the economy, businesses, and the population. Special attention was payed to the support of the unemployed and the job searches simplification. For instance, remote registration on the labor exchange was introduced, allowing citizens to apply for unemployment registration and receive benefits through the online portal without violating the self-isolation regime[1]. This measure remained in effect until December 31, 2021 (Government of the Russian Federation 2020a). Additionally, the maximum unemployment benefit amount was increased from 8,000 to 12,130 rubles (Government of the Russian Federation 2020b). The period for increasing the minimum unemployment benefit (up to 4.5 thousand rubles) was extended from May 1 to August 31, 2020 (The State Duma 2020). Sole proprietors (individual entrepreneurs) who ceased their activities after March 1, 2020, and were recognized as unemployed were also eligible to apply for the maximum unemployment benefit (12,130 rubles) for a period of up to 3 months (Government of the Russian Federation 2020c). Free retraining programs were organized for individuals who lost their jobs during the pandemic, with the government allocating additional funds for the expansion of educational programs (Government of the Russian Federation 2020d). This measure aimed to assist the people affected by the crisis in acquiring in-demand skills. Furthermore, individuals who lost their jobs after March 1, 2020, were eligible for unemployment benefits in the maximum amount for 3 months, along with additional payments of 3,000 rubles for each minor child being raised by the unemployed individual (Government of the Russian Federation 2020e). Those people whose unemployment benefit payment period ended after March 1 were given the opportunity to extend their payments for additional 3 months while maintaining the same benefit amount (Government of the Russian Federation 2020f).

Thus, during the pandemic, the state provided significant support to the population and enterprises in order to mitigate the consequences of the coronavirus crisis.

Review of empirical research

As noted (Kapelyushnikov 2022), during periods of crisis in Russia, mechanisms for wage adjustment (price adjustment) and reduction of working hours (temporary adjustment) were found to be more effective than layoffs. During the coronavirus crisis of 2020, the extent of layoffs was moderate. The author describes the mechanisms of labor market adjustment in Russia, comparing data from the HSE survey for the end of 2019 and the end of 2020. The findings show a heterogeneous effect: in terms of sectoral context, agriculture and public administration were the most protected in terms of layoffs, while in the context of age, the young (under 25 years old) were the most affected, which aligns with the results of the paper (Kartseva and Kuznetsova 2020).

Gimpelson (2022) uses Rosstat data to show a simultaneous decrease in both the hiring rate and the retirement rate in the second quarter of 2020 compared to the second quarter of 2019. Enterprises froze both layoffs and hiring during this period. Coupled with the fact that a small percentage of RLMS respondents applied for unemployment benefits while seeking work, this indirectly supports the claim that the increase in unemployment benefit applications in the second quarter of 2020 is partly due to free-riders. For more information on the concept of free-riders in the context of consuming public goods, see (Baumol 2004).

1 Note that currently, in 2023, remote filing of an application for recognition as unemployed is possible, but obtaining the status of unemployed can only be accomplished with a personal visit to the Employment Center.

Several foreign studies, starting with (Chetty 2020), have examined the response of unemployment to support measures and the implementation of quarantine measures at both the national level (e.g., in Australia, where unemployment increased by 1.7% according to calculations by Guven et al. (2020)) and the regional level. Hassink et al. (2020), using panel data based on weekly data for 2019 and 2020 and employing the difference-in-differences method, found that in the Netherlands, restrictive measures had a greater impact on the labor market (unemployment, weekly working hours, hourly wages) than regional incidence, with young people (under 20 years old) and individuals without permanent contracts being the most vulnerable.

The study by Baek et al. (2021) assesses the effect of the implementation of restrictive measures (stay-at-home orders, SAH) in the United States on the increase in applications for unemployment benefits using weekly state-level data. In their primary model, the authors estimate a cross-sectional regression where the total number of benefit applications in each state for the period under review is the dependent variable, adjusted by the number of employees in the state. The binary variable indicating the effect of the implementation of restrictive measures is set to one if the state imposed restrictions «early» (before April 4, 2020), and zero otherwise, capturing the non-simultaneous staggered implementation of restrictions. An alternative specification evaluates a panel model with Two-Way Fixed Effects based on weekly data. Controlling for other factors, local restrictive measures increased the number of weekly applications by 1.9%. In total, approximately 17 million applications for unemployment benefits were filed in the United States between March 14 and April 4, 2020, due to quarantines.

Researchers in (Gupta et al. 2020) also reach a similar conclusion regarding the significant impact of restrictive measures (SAH and ABC – any business closure) on the decline in employment in the United States. They use the difference-in-differences method and an event study design over a shorter period. The study finds that for every subsequent 10 days of restrictive measures, employment is reduced by 1.7%.

Most researchers primarily focus on evaluating the effects of the implementation of restrictive measures and their duration. In contrast, the current paper assesses the effect of the removal of restrictive measures in Russian regions, which occurred at different times and not simultaneously.

Data

By regional restrictive measures, we refer to the restrictions imposed by regional authorities at the local level, including sanitary and epidemiological measures, limitations on social contacts, and restrictions on business operations. The focus of our evaluation is on the effect of removing these restrictive measures, rather than their introduction. This choice is influenced by the nature of the data we use.

The main measures aimed at limiting social contacts among citizens were implemented starting from March 2020 (Figure 1):

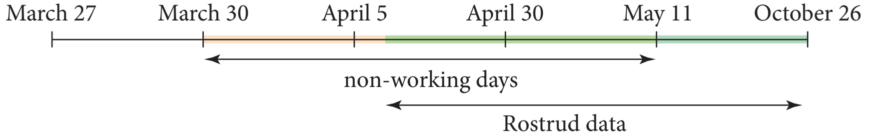

Figure 1. Timeline of available data. *Source*: Compiled by the authors.

Here is a summary of the key regional restrictive measures implemented in Russia:

- March 27: Decree of the Government of the Russian Federation No. 346 sets the minimum and maximum amounts of unemployment benefits for 2020.
- March 30: Restrictions on the movement of residents and the introduction of a self-isolation regime for all citizens of the Russian Federation.
- March 30 – April 5: The head of state addresses the nation regarding the spread of the coronavirus and announces a non-working week with wage preservation.
- April 5 – April 30: Extension of the non-working days regime. Regional authorities are granted additional powers to decide the measures to combat the coronavirus in their respective regions and modify the list of industries with suspended activities.
- April 30 – May 11: The last extension of the non-working days in 2020.

The availability of data on the number of applications for unemployment benefits starts from April 6, 2020, due to the transition to a digital system for submitting applications through the «Jobs in Russia» portal. Since the initial restrictions were introduced simultaneously in all regions on March 30 during the President's address, we lack information on the earlier dynamics of registered unemployment and do not have a control group to assess the effect of the introduction of restrictive measures.

Besides the data on the labor market provided by ANO «CPMS" (Center of Prospective Management Solutions), we collected data on restrictive measures introduced or lifted by the heads of the Russian Federation's regions, depending on the epidemiological situation in each region. The data was gathered from an interactive map on the official website aimed at informing the public about the coronavirus[1]. To indicate the severity of the current restrictive measures in each region, Rospotrebnadzor (The Federal Service for Surveillance on Consumer Rights Protection and Human Wellbeing) utilized a four-stage classification system, where "stage 0" represented the strictest restrictions, and "stage 3" denoted the mildest. The transition to a new stage of restrictions was based on information regarding the infection rate, the availability of beds for COVID-19 patients, and testing coverage (TASS 2020). In our calculations, we converted the degree of restriction severity into a binary variable. It takes a value of zero for stages "0" and "1" and a value of one for the remaining stages of restrictive measures.

The data we collected has been available since June 8, 2020, as there was no prior publication of information about the restrictions. Figure 2 illustrates the dynamics of the lifting of restrictive measures in the Russian regions. It is important to note that unlike the introduction of measures, the lifting of restrictions did not occur simultaneously in different regions. Local authorities independently made decisions to ease the restrictive measures. Additionally, there were no instances of returning to stricter restrictions during the period under review. Therefore, we are dealing with a staggered adoption of the measures.

To assess the effects of the removal of regional restrictive measures, we utilize a dataset on registered unemployment during the pandemic, collected by Rostrud and the Central Bank[2]. The data is provided on a weekly basis, covering a total of 30 weeks from April 6, 2020, to October 26, 2020.

1 Stopkoronavirus.rf portal. The COVID-19 situation in the regions can be found at https://стопкоронавирус.рф/information/ (accessed on December 13, 2020). At the time of writing the manuscript, the map displayed data on newly reported cases of coronavirus in the regions. To familiarize yourself with the type of map we used in the study, you can visit the web archive of the page at the following link: http://web.archive.org/web/20200615124941/https://xn--80aesfpebagmfblc0a.xn--p1ai/information/

2 «Registered unemployment in Russia: depersonalized microdata on the characteristics of citizens and services received for 2017-2021.» Rostrud; processing: Infrastructure of research data, ANO «CPUR», 2021.

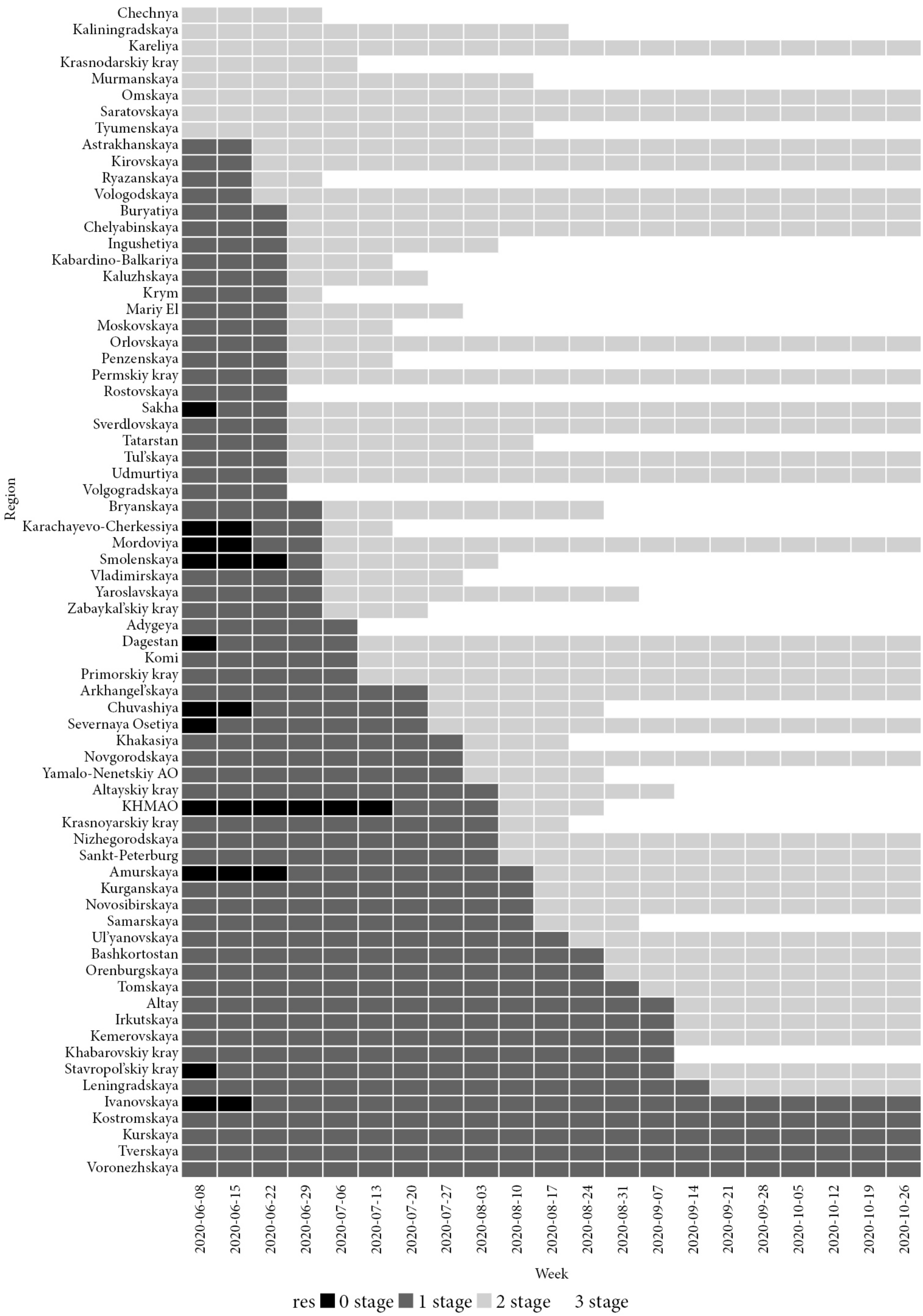

Figure 2. Stages of lifting coronavirus restrictions in the regions of the Russian Federation, 2020. *Source*: Compiled by the authors based on data from the stopkoronavirus.rf (стопкоронавирус.рф) website.

The Rostrud dataset consists of 4,947,059 observations, which initially contained duplicate applications. These duplicates, approximately 450,000 observations, were removed from the dataset. The duplicates often occurred when applicants did not complete the application form entirely and subsequently submitted it again. Among the remaining duplicates, applications that underwent the process of recognizing the applicant as unemployed were selected. The microdata was then aggregated based on the "region-industry-week" breakdown. Applications that lacked information on the previous occupation , as per the IAS AVB (Information and analytical system all-Russian database of vacancies) handbook "Jobs in Russia," were not considered in the analysis.

To ensure the consistency of the data, observations from the Chukotka and Nenets Autonomous Okrugs were excluded from the dataset due to their low number of unemployment benefit applications, including weeks with zero applications. This exclusion is crucial when using logarithmic specifications of variables. Observations from Moscow were also excluded due to its unique characteristics compared to other regions of Russia, such as higher average income, stricter control measures for COVID-19 compliance, and more extensive population testing. Furthermore, observations corresponding to the "Early career" and "Logistics" categories, as per the IAS AVB handbook "Jobs in Russia," were excluded due to their limited number of observations (167 and 56, respectively). Additionally, applicants from the "Early career" category may differ from the rest of the sample in terms of initial characteristics and their response to the crisis. Therefore, the final sample consists of 4,246,341 applications. Figure 3 illustrates the weekly dynamics of applications from the sample, encompassing all regions.

As seen from Figure 3, there is a traditional seasonal increase in the number of job seekers in September. This supports the argument for limiting the data analysis to the end of August 2020.

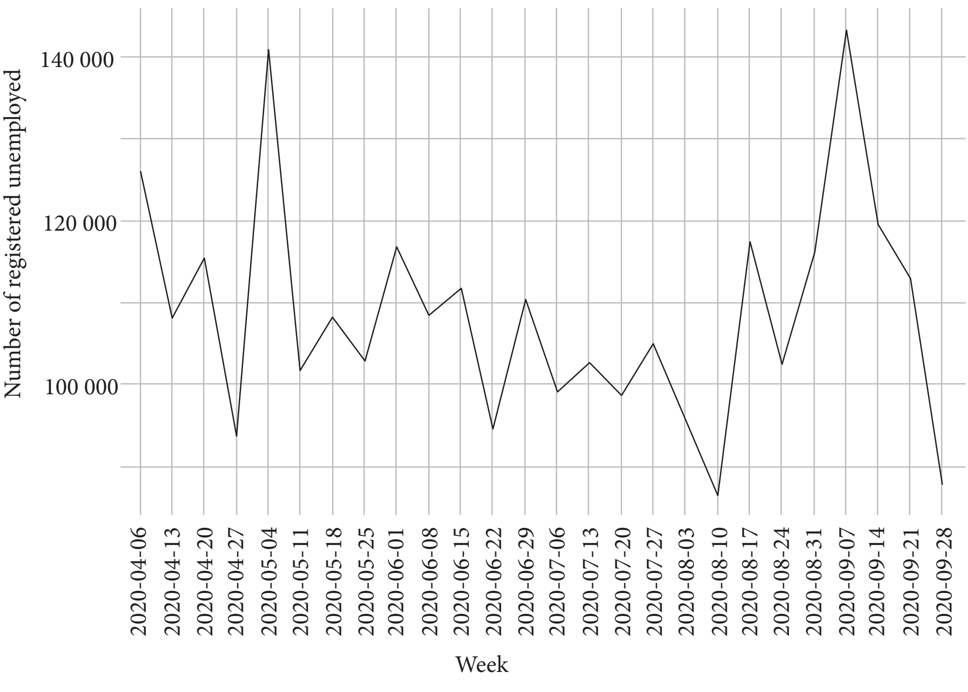

Figure 3. Weekly dynamics of approved applications for unemployment benefits in the sample. *Source*: Compiled by the authors.

Descriptive statistics for the sample are presented below (Table 1).

Table 1. Descriptive statistics

Variable	Average	Median	Minimum	Maximum	St. dev.
Number of applications for unemployment benefits in the region	1780.4	1116	20 (Altai Republic, 1st week of June)	42 096 (Kemerovo Oblast, 2nd week of June)	2398.6
Level of restrictions in the region, discretely from 0 to 3	1.91	2	0	3	0.78
Population at the beginning of 2020, people	1 362 400	1 192 500	140,150	7 690 900	1 362 400

Source: Compiled by the authors.

Model

In order to obtain a meaningful estimate of the national average effect of the removal of restrictive measures, it is necessary to choose a method that accurately captures dynamic effects. We employ several approaches to evaluate the treatment effect, taking into account the staggered data structure. These approaches include a model with Two-Way Fixed Effects, the Callaway and Sant'Anna method (Callaway and Sant'Anna 2021), the Boryusyak and co-authors' method (Borusyak et al. 2022), and the Sun and Abraham method (Sun and Abraham 2021).

All of these approaches are based on the following regression equation (presented in accordance with (Sun and Abraham 2021)):

$$\log Y_{it} = \sum_{k}^{K} \tau_k \cdot I\left[t - G_i = k\right] + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where $\log Y_{it}$ represents the logarithm of the number of new applications for unemployment benefits in region i in week t.

$I[t - G_i = k]$ is a binary indicator that takes the value 1 if the expression in parentheses is true. It checks whether the difference between the current week t and the week when restrictions were lifted in region i (G_i) is k weeks.

K represents the maximum number of weeks after the restrictions are lifted. In our study, $K = 8$, corresponding to a period of 2 months.

τ_k represents the treatment effect on the k-th week since the lifting of restrictions. For $k < 0$, the coefficients are interpreted as a test of the parallel trends assumption. This tests the hypothesis that k weeks before the lifting of restrictions, there is no significant difference in the dynamics of applications for benefits between the regions in the treatment group (where regional restrictions have been lifted) and the regions in the control group (where restrictive measures are still in effect). In our study, the minimum value of k is -8.

μ_i, λ_t are the fixed effects for region i and period (week) t, respectively.

ε_{it} represents the random shock or error term.

The primary method used to assess the treatment effect on panel data is the Two-Way Fixed Effects (TWFE) model. In this case, when $K = 1$, the coefficient is estimated for a binary variable indicating the cancellation of COVID restrictions.

$$\log Y_{it} = \beta^{DD} \cdot D_{it} + \mu_i + \lambda_t + \varepsilon_{it} \qquad (2)$$

In the equation, $\log Y_{it}$ represents the logarithm of the number of new applications for unemployment benefits in region *i* in week *t*.

D_{it} is a binary indicator that takes the value 1 if, since the lifting of restrictions, the region belongs to the treatment group (regions where restrictive measures were lifted in the considered interval).

β^{DD} represents the effect of the cancellation of restrictions, which is assumed to be the same for all regions and time periods in this model.

μ_i, λ_t are the fixed effects for region *i* and period (week) *t*, respectively.

ε_{it} represents the random shock or error term.

This method has certain limitations when the cancellation of COVID restrictions follows a staggered structure, where regional authorities lift restrictions at different times (as shown in Figure 2). The TWFE method assumes a "block" structure in the "region-week" matrix, where regions in the treatment group simultaneously lift restrictions, allowing for the interpretation of the average treatment effect on the treated (ATT).

However, in the case of a staggered structure, the TWFE method assigns different weights to regions depending on the timing of the lifting of COVID restrictions. Goodman-Bacon (2021) addresses this issue by considering a scenario with three periods and three groups of regions: regions that consistently remain in the control group throughout the three periods, regions that transition early to the treatment group (between periods 1 and 2), and regions that transition late to the treatment group (between periods 2 and 3). He proves a theorem called the "Bacon decomposition," which states that the estimated coefficient $\hat{\beta}^{DD}$ from Model (2) is equal to the weighted average of four estimates.

$$\hat{\beta}^{DD} = s_1 \cdot \hat{\beta}^{EU} + s_2 \cdot \hat{\beta}^{LU} + s_3 \cdot \hat{\beta}^{EL,1-2} + s_4 \cdot \hat{\beta}^{EL,2-3} \qquad (3)$$

where $\hat{\beta}^{EU}$ represents the estimate obtained using the difference-in-differences method for periods 1 and 2 when comparing regions that transitioned "early" to to the treatment group with regions from the control group;

$\hat{\beta}^{LU}$ represents the estimate obtained using the difference-in-differences method for periods 2 and 3 when comparing regions that transitioned "late" the treatment group with regions from the control group;

$\hat{\beta}^{EL,1-2}$ represents the estimate obtained using the difference-in-differences method for periods 1 and 2 when comparing regions that transitioned "early" to the treatment group with regions that transitioned "late" to the treatment group. In this case, the control group consists of regions that transitioned to the treatment group "late" and have not changed their status between periods 1 and 2.

$\hat{\beta}^{EL,2-3}$ represents the estimate obtained using the difference-in-differences method for periods 2 and 3 when comparing regions that transitioned "early" to the treatment group with regions that transitioned "late" to the treatment group. In this case, the control group consists of regions that transitioned "early" to the treatment group and have not changed their status between periods 2 and 3.

s_1, s_2, s_3, s_4 represent the weights assigned to the corresponding estimates, which depend on the size of the groups being compared and the sample variance of the variable D_{it} (derived from the theorem).

Therefore, according to the Bacon decomposition, regions that lifted restrictions early will initially be interpreted as a treatment group by the TWFE method (when estimating

$\hat{\beta}^{EU}$ and $\hat{\beta}^{EL,1-2}$), and towards the end of the observed period, they will be interpreted as a control group (when estimating $\hat{\beta}^{EL,2-3}$).

This type of comparison, as described by Roth et al. (in press), is referred to as counterintuitive or "forbidden," indicating that in such a situation, some observations corresponding to several weeks after the lifting of restrictions may have negative weights. According to the Frisch-Waugh-Lovell theorem, the estimate $\hat{\beta}^{DD}$ from model (2) can be obtained using a two-step procedure.

The first step involves evaluating the model that captures the dependence of the binary variable D_{it} on the fixed effects of the region and the period (week):

$$D_{it} = \mu_i + \lambda_t + u_{it} \tag{4}$$

Where u_{it} is a random shock.

At the second step, regression $\log Y_{it}$ is estimated depending on the residuals from the model (4):

$$\log Y_{it} = \beta^{DD} \cdot (D_{it} - \widehat{D}_{it}) + \varepsilon_{it} \tag{5}$$

where $(D_{it} - \widehat{D}_{it})$ are the residuals from the first step model (4), and $\widehat{D}_{it}$ are the calculated values from the first step model (4).

Thus, the OLS estimate of the parameter from the model (5) can be represented as:

$$\hat{\beta}^{DD} = \frac{\sum_{i,t}\left[\left(D_{it} - \widehat{D}_{it}\right) \cdot \log Y_{it}\right]}{\sum_{i,t}\left[D_{it} - \widehat{D}_{it}\right]^2} \tag{6}$$

Since the regression equation (4) is estimated using a linear probability model, the predicted values $\widehat{D}_{it}$ may fall outside the range [0, 1]. Consequently, $(D_{it} - \widehat{D}_{it}) < 0$, resulting in negative weights in equation (6) for the corresponding $\log Y_{it}$. Each value $\log Y_{it}$ can be written as the sum $\log Y_{it}(\infty)$ (the logarithm of the number of applications for unemployment benefits under the current restrictive measures) and $\tau_{it}(g)$ (the effect of lifting restrictive measures for region i in period t, if the lifting of restrictions in the region occurred at time g). As a result, observations corresponding to several weeks after the lifting of restrictions, and therefore the effects of lifting restrictive measures for these observations, may have negative weights. These characteristics make it challenging to accurately interpret the TWFE estimate.

The peculiarity of methods that account for the non-simultaneous (staggered) lifting of restrictions in regions is that they evaluate individual effects for each region-week pair and average them in different ways.

For example, Callaway and Sant'Anna (2021) introduce $ATT(g,t)$ as the average treatment effect on the treated for period t among the regions that lifted COVID restrictions at time g. It is defined as follows:

$$ATT(g,t) = E\left(\log Y_{it}(g) - \log Y_{it}(\infty) \middle| G_i = g\right), \tag{7}$$

where $\log Y_{it}(g) - \log Y_{it}(\infty)$ is the difference between the potential outcomes: the logarithm of the number of applications for unemployment benefits in region i in period t if the cancellation of COVID restrictions occurred at time g, and if the cancellation of restrictions by time t did not occur.

If the assumption of parallel trends in applications for unemployment benefits across all groups is observed until the restrictions are lifted, as well as the assumption of "no anticipation" (i.e., the trend remains unchanged upon receiving information that COVID restrictions will be lifted in the future), this effect can be expressed as follows:

$$\widehat{ATT(g,t)} = \frac{1}{N_g} \sum_{i:G_i=g} \left[\log Y_{it} - \log Y_{ig-1} \right] - \frac{1}{N_{\text{contr}}} \sum_{i \in \text{contr}} \left[\log Y_{it} - \log Y_{ig-1} \right] \quad (8)$$

Where N_g is the number of regions that abolished COVID restrictions at time g.

N_{contr} – the number of regions in the control group, i.e. not-yet-treated by time t.

$\log Y_{it} - \log Y_{ig-1}$ – the difference between the logarithm of the number of new applications for benefits during week t and during the week before the restrictions were lifted (g – 1).

The method of K.Borusyak (Borusyak et al. 2022) evaluates the TWFE model for regions that have not yet abolished COVID restrictions (i.e. when $t < g$):

$$\log Y_{it}(\infty) = \mu_i + \lambda_t + \varepsilon_{it} \quad (9)$$

where ∞ means that in region i, the cancellation of restrictions had not occurred by t.

Then, for each region i in the period $t \geq g$ when COVID measures are canceled, the $\log \widehat{Y_{it}}(\infty)$ forecast is calculated according to the model (9). The difference $\log Y_{it} - \log \widehat{Y_{it}}(\infty)$ is interpreted as the difference between the potential outcomes: what would the logarithm of the number of applications for unemployment benefits in region i in period t be if the cancellation of COVID restrictions occurred at time g, and if the cancellation of restrictions by time t did not occur. Then each difference is substituted in (8).

Thus, the difference between the methods lies in the way the control group is formed. In the Callaway & Sant'Anna method, the comparison is made with the last week before the lifting of restrictive measures, while in the Borusyak method, it is made with the average value for all periods before the lifting of restrictions. The Sun & Abraham method also evaluates equation (8), but the control group consists of either regions that have never lifted COVID restrictions during the period under review (never-treated), if such regions exist in the sample, or regions that were the last to remove restrictions (last-to-be-treated).

In this study, we weigh the effect estimates $\widehat{ATT(g,t)}$ in order to obtain the dynamic average treatment effect, which represents the average change in the number of new applications for unemployment benefits after k weeks following the lifting of restrictions.

Finally, it should be clarified that our aim is to estimate the average effect for the country as a whole rather than the average effect for each region . This distinction becomes important when averaging regions of different sizes. For example, if a "small" region has a treatment effect of 10 percentage points, and a "large" region has a treatment effect of 0 percentage points, we want to obtain an average effect weighted by the population size of each region. To achieve this, in addition to the basic model, we also consider a model that incorporates population weights based on the region's population at the beginning of 2020.

Estimation results

The dynamic effect of removing restrictions on new applications for unemployment benefits, expressed as a percentage of the last day of restrictions, was estimated using a Two-Way Fixed Effects model. Two specifications were considered: one based on the number of applications and another weighted by the population of each region at the beginning of 2020, in order to ensure robustness of the results.

Figure 4 shows the estimated effects for each week up to August 31, which marks the end of the period of increasing the minimum unemployment benefit. In all specifications, the effect of removing restrictions on the dynamics of approved applications for unemployment benefits is not statistically significant. This is indicated by the fact that the 95% bootstrap confidence interval includes zero, suggesting that there is no significant effect.

However, Figure 5 reveals an interesting observation. In the Two-Way Fixed Effects model, observations corresponding to 9-12 weeks after the removal of restrictions are assigned negative weights. This raises a concern and indicates the need to further validate the calculations using the staggered difference-in-differences method.

It is important to conduct additional analyses and consider alternative approaches to assess the effect of removing restrictions on unemployment benefit applications, particularly for the period beyond 9-12 weeks post-removal, in order to gain a comprehensive understanding of the dynamics and to ensure the reliability of the findings.

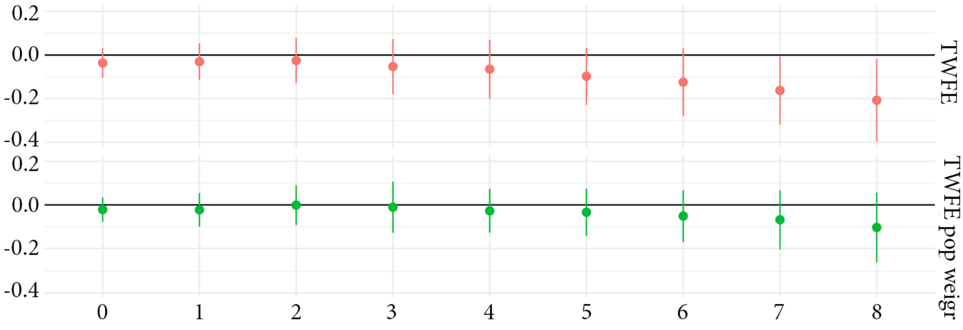

Figure 4. Effect of the removal of regional restrictive measures by week on the dynamics of applications for unemployment benefits, on average in Russia, a model with Two-Way Fixed Effects. *Source:* Compiled according to the authors' calculations.

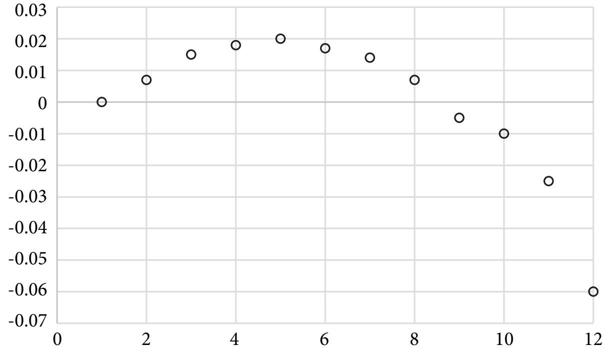

Figure 5. Weights for observations for weeks 1 to 12 after the restrictions are lifted, a model with Two-Way Fixed Effects. *Source:* Compiled according to the authors' calculations.

In this regard, three modifications of staggered difference-in-differences model are also estimated: the modification of Callaway & Sant'Anna (2021), Borusyak et al. (2022), and Sun & Abraham (2021) (Figures 6, 7, 8, respectively).

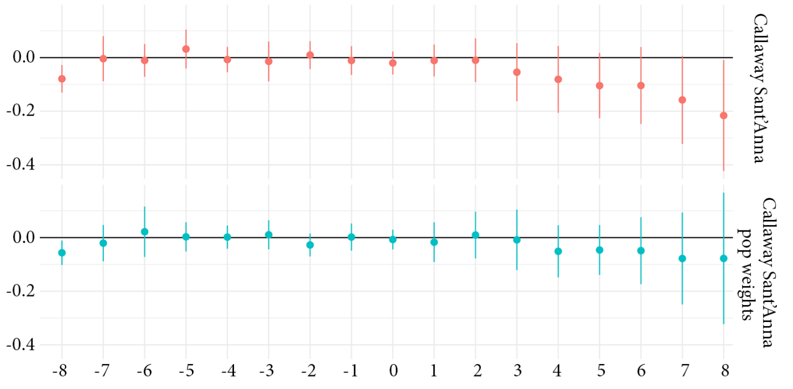

Figure 6. The effect of the removal of regional restrictive measures by week, on average in Russia, staggered difference-in-differences model, Callaway & Sant'Anna modification (2021). *Source:* Compiled according to the authors' calculations.

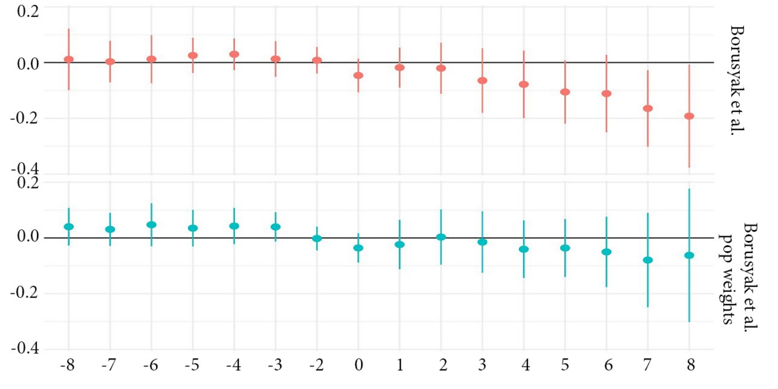

Figure 7. The effect of the removal of regional restrictive measures by week, on average in Russia, staggered difference-in-differences model, Borusyak et al. modification (2022). *Source:* Compiled according to the authors' calculations.

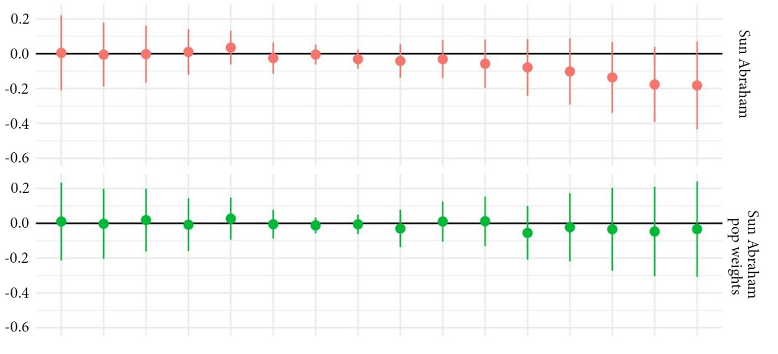

Figure 8. Effect of removal of regional restrictive measures by week, on average in Russia, the staggered difference-in-differences model modification by Sun & Abraham (2021). *Source:* Compiled according to the authors' calculations.

In all specifications, the effects of removing restrictions are insignificant, which may have several explanations.

Firstly, during the period under review, increased unemployment benefits were paid, which could stimulate new applications and offset the effect of lifting restrictions. It is impossible to use data for the period after August 31, 2020 (i.e., after the end of the period of payment of the increased benefit) separately because, according to the data from the stopcoronavirus website, only 6 regions of the Russian Federation lifted restrictions (moved to the second stage of lifting restrictions) after August 31, and 5 more were not lifted until the end of the period under review. In other words, a sample of this size does not allow us to obtain accurate estimates.

Secondly, on the other hand, according to Gimpelson's calculations (2022) based on RLMS data, by July-August 2020, the hiring intensity had recovered to the level of February-March. However, only one in ten respondents answered that they used unemployment benefits as a source of material support. Therefore, the dependent variable in our study estimates only a small portion of those affected in 2020.

Thirdly, in the present study of the binary treatment variable represents the transition from the first to the second stage of lifting restrictions was encoded according to the data from the stopkoronavirus.rf website. At the first stage, the work of enterprises in the service sector and trade in non-food products was allowed, subject to certain requirements such as area limitations, separate entrances, etc., as well as outdoor sports. Consequently, the transition between the stages could not have been as significant, while the most stringent restrictive measures operated beyond the available data (until June 2020). This means that it is impossible to establish symmetry in the reaction of applications for unemployment benefits when introducing and removing restrictions. Additionally, the data used lacks sufficient observations corresponding to the zero stage of removing restrictions (Figure 2) for accurate estimates.

Finally, it is possible that the observed data on existing restrictions did not fully reflect the real business activity (or recession) in the economy.

To check the robustness of the results, similar calculations were carried out using an alternative binary treatment variable corresponding to the operation of the digital pass regime in the region. Data on the timing of the introduction and cancellation of digital passes were collected from various sources, including regional news sites[1] and materials prepared by experts from the company "Garant" (Garant 2020). An example of the results is shown in Figure 9.

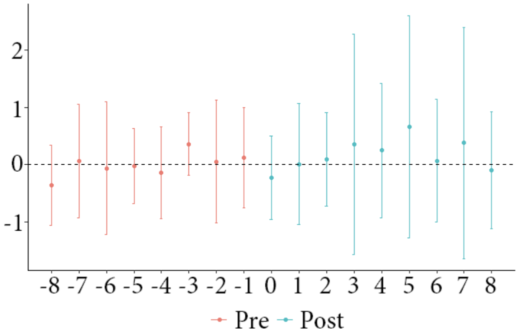

Figure 9. The effect of the abolition of the digital pass regime in the region on the dynamics of applications for unemployment benefits by week on average in Russia, staggered difference-in-differences model, modification by Callaway & Sant'Anna (2021). *Source:* Compiled according to the authors' calculations.

1 Dates and links to news pages are collected in a table posted in the repository by link https://github.com/annastavniychuk/russia_covid_lockdowns

In all previous calculations, insignificant results were obtained. Additionally, it should be noted that in all specifications, the confidence intervals for coefficients at $k < 0$ contain zero, indicating the presence of parallel pre-trends. This suggests that, k weeks before the lifting of restrictions, there is no significant difference in the dynamics of applications for unemployment benefits between the regions in the treatment group and the control group.

To further investigate the effect of restrictions, we incorporate additional data – the Yandex self-isolation index. This index provides an indication of the level of self-isolation observed, with higher values indicating better adherence to self-isolation measures. The index is calculated using depersonalized data from various Yandex applications, such as Yandex Navigator, Yandex Metro, Yandex.Ether, Zen, KinoPoisk, and others. These indicators are scaled, with 0 representing typical rush hour levels on a weekday, and 5 representing indicators typically observed during late-night hours (Yandex 2020b).

The Yandex dataset covers the period from 14th December 2020 to 10th August 2022, which allows us to supplement the previous data used in our analysis.

Yandex analysts give the following scale of population activity (Yandex 2020a):

- 0-2.4 points – maximum number of people outdoors;
- 2.5-2.9 points – there are a lot of people outdoors;
- 3-3.5 points – there are some people outdoors;
- 3.6-3.9 points – most people are at home;
- 4-5 points – there is almost no one outdoors.

Following the same methodology in our paper we examined how the actual activity of the population correlates with the official statistics on the stages of restrictive measures according to the stopcoronavirus portal. We constructed three graphs similar to Figure 2 (see Figures 10, 11 and 12 in the Appendix[1]). In Figure 10, we observe that people were cautious and adhered to the necessary recommendations for self-isolation for some time (lilac and turquoise cells corresponding to the range from 3 to 3.9 points). However, by May 4-11, in all regions of the country, people began to behave as they did before the coronavirus restrictions, venturing out in large numbers. The visualization of the Yandex self-isolation index and the actual stages of coronavirus restrictions (Figure 11 in the Appendix) demonstrated that even during the strictest restrictions of the zero stage in some regions from June 8 to July 6 (Figure 11), there were still many people on the streets (Figure 10), comparable to pre-coronavirus restriction levels. This indirectly confirms that, on the one hand, the self-isolation regime was not strictly observed, and on the other hand, it may have neutralized the effect of the economic lockdown, allowing for a certain level of economic activity to be maintained.

As additional results, we obtained static estimates (at $K = 1$) of the effect of lifting regional restrictions by industry, according to the IAS AVB handbook "Jobs in Russia," on the number of new approved applications for unemployment benefits. Table 2 presents the estimates for several industries along with a 95% bootstrap confidence interval.

As observed from Table 2, a significant decrease in the number of new applications for unemployment benefits is evident in the sectors of hotels and catering establishments, activities in the field of culture, sports, leisure, and entertainment, as well as in the provision of other types of services. These findings align with economic intuition and are in line with some other studies (Kim and Kim 2022; Forsythe et al. 2020).

1 Figures 11 and 2 differ from each other only by the location of the regions along the ordinate axis: in Figure 2, the regions are arranged according to the gradation of exit from restrictions, and in Figure 11 alphabetically for ease of comparison with Figure 10.

Table 2. Assessment of the effect of the abolition of regional restrictions in a number of industries

Branch	Effect Size, %	Confidence interval 95%
Activities of hotels and catering establishments	-0.191	(-0,355, -0,027)
Activities in the field of culture and sports, leisure and entertainment	-0.137	(-0,236, -0,038)
Professional, scientific and technical activities	–0.087	(-0,206, 0,032)
Transportation and storage	–0.070	(-0,163, 0,023)
Manufacturing industries	–0.034	(-0,091, 0,023)
Administrative activities and related additional services	0.005	(-0,05, 0,06)
Wholesale and retail trade; repair of motor vehicles and motorcycles	0.010	(-0,065, 0,085)
Public administration	0.082	(-0,153, 0,317)

Source: Compiled by the authors.

Conclusion

This study aims to evaluate the changes in the dynamics of applications for unemployment benefits in response to the removal of regional restrictive measures during the first wave of COVID-19 spread in Russia. On average, there is no significant change observed in this indicator. This result remains consistent across various specifications, including a model with Two-Way Fixed Effects, different modifications of the staggered difference-in-differences method, and the use of an alternative indicator of the effect of restrictive measures (the duration of digital passes instead of the region's transition to the second stage of restrictions removal).

The number of new applications did not show a significant decrease, which implies that the surge in applications for unemployment benefits in 2020 could be attributed to factors such as increased benefits and simplified procedures for obtaining them.

However, it is important to acknowledge several limitations in this research. Firstly, the assessment relies on the assumption of symmetry in the reaction to the introduction and removal of restrictive measures. Secondly, during the period under review, increased unemployment benefits were still being paid. Thirdly, this study provides an evaluation of only one mechanism of labor market adaptation during the pandemic. Additionally, the study highlights the discrepancy between formal restrictive measures and the actual economic activity, as reflected in the Yandex self-isolation index.

There are several potential ways for expanding this research. For instance, researchers can use a similar methodology and a database[1] of restrictive measures collected by the authors, on the "region-week" breakdown for 2020, to assess the effect of the duration of restrictions on various indicators of economic activity.

1 The database of restrictive measures in the context of «region-week» is presented in the repository via the link https://github.com/annastavniychuk/russia_covid_lockdowns

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Appendix

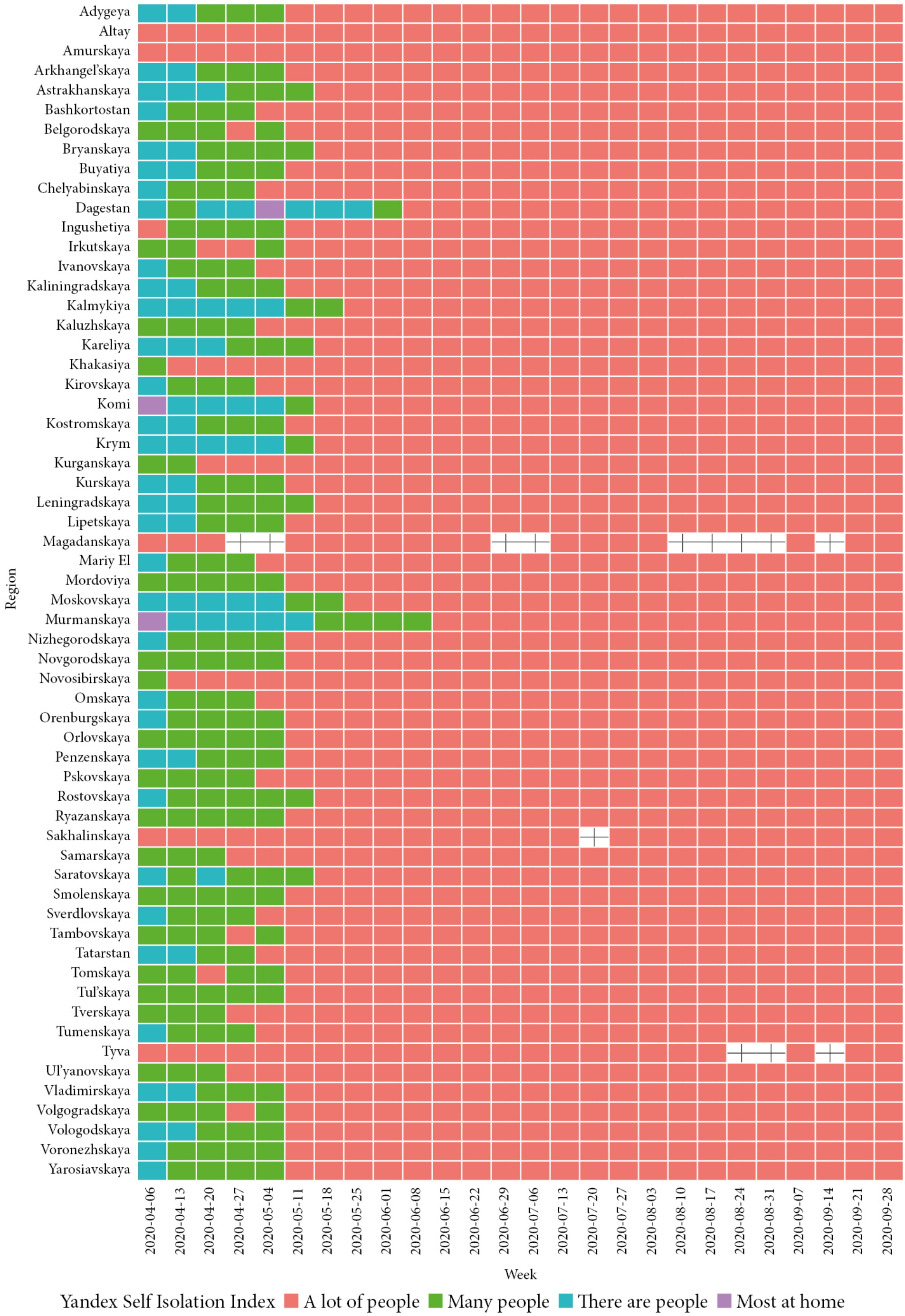

Figure 10. Yandex Self-isolation Index by region and week from April 6 to September 28, 2020. *Source:* Compiled by the authors according to Yandex data.

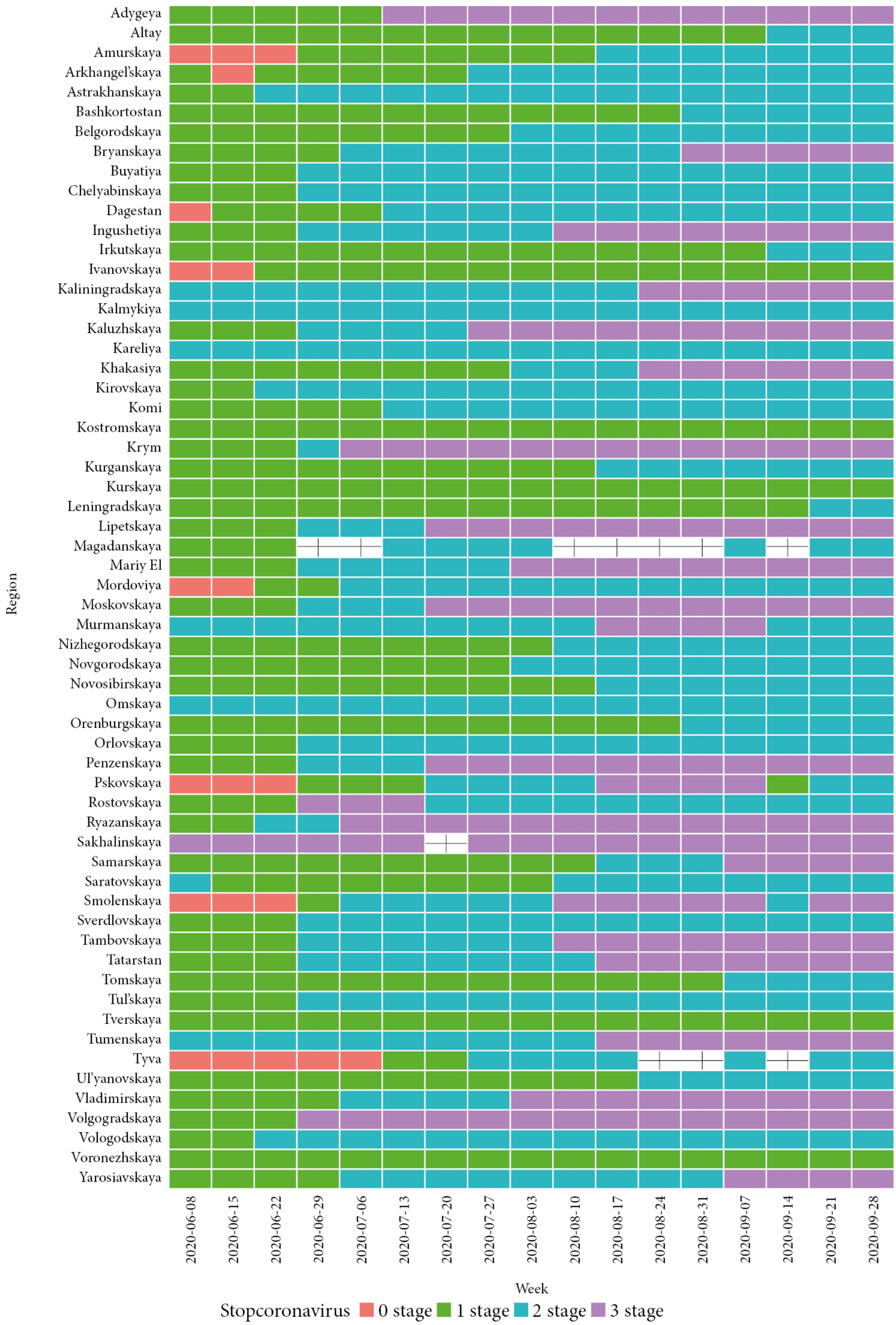

Figure 11. Stages of removal of coronavirus restrictions in the subjects of the Russian Federation, 2020. *Source*: Compiled by the authors using data from the stopkoronavirus.rf website.

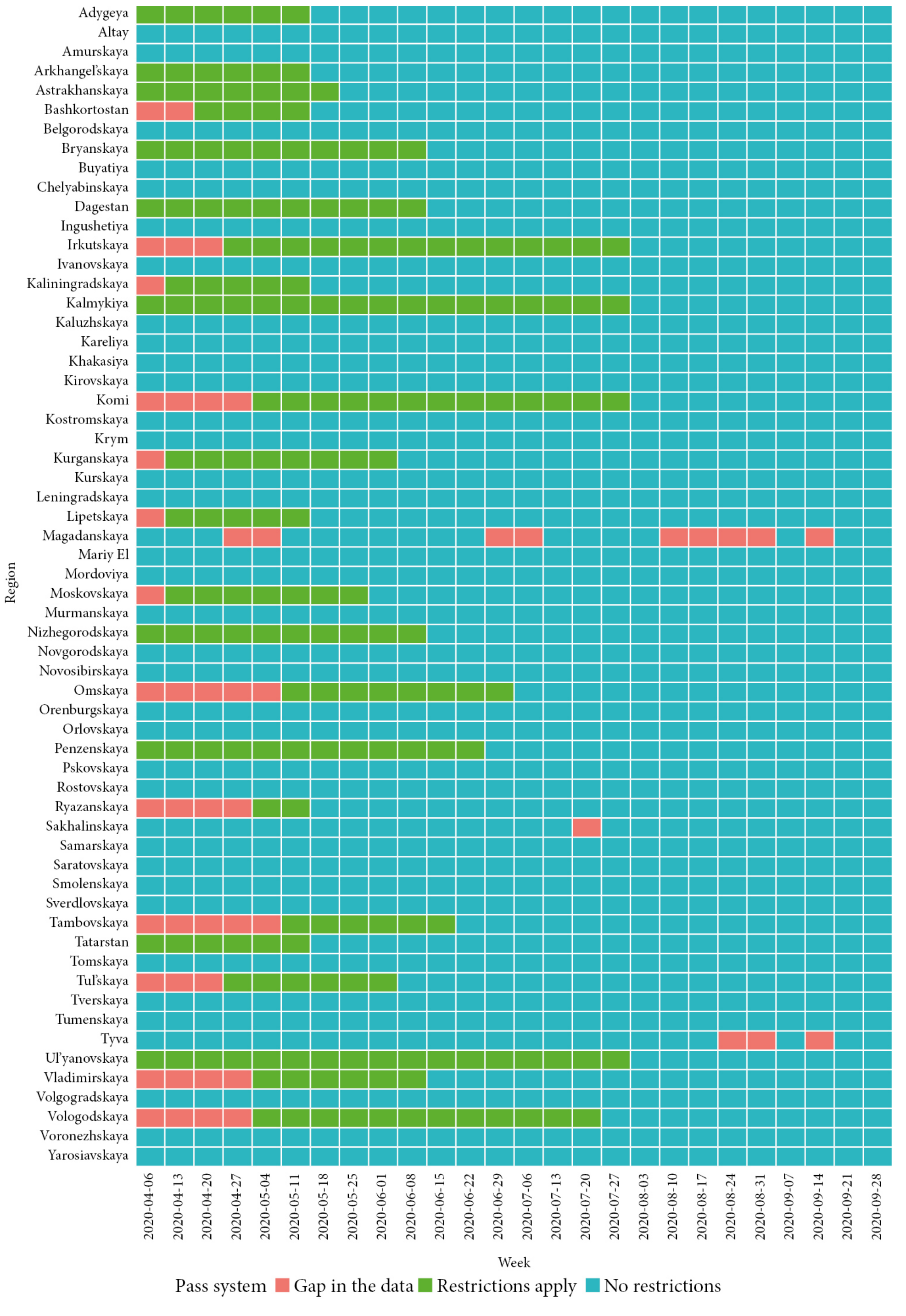

Figure 12. Introduction of restrictions on movement in the regions of the Russian Federation, 2020. *Source*: Compiled by the authors using normative legal acts.

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