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Exploring the hidden impact of the Covid-19 pandemic: The role of urbanization☆

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A B S T R A C T

We examine the role of residential environments (urban/rural) in understanding the impact of the COVID-19 pandemic and the restrictions in nationwide movement on several socio-economic attitudes. We conducted large-scale surveys in four European countries (France, Germany, Spain, and the United Kingdom) before and after nationwide lockdowns were implemented. We investigate how the pandemic affected: (i) economic (economic insecurity), (ii) political (trust in domestic and international institutions), and (iii) social attitudes (loneliness), by controlling for the degree of urbanization, obtained from the geocodes of the survey respondents. Our results show that taking the degree of urbanization into account is not only relevant but is also essential. Compared to urban areas, in rural areas lockdowns led to a greater increase of economic insecurity and to a greater decrease in trust in domestic institutions. We also show that these results are particularly valid for women and households with children.

1. Introduction

The earliest recorded pandemic afflicted Athens during the Peloponnesian War in 430–427 B.C. Since then, a long list of pandemics (such as smallpox, measles, bubonic plague, influenza, etc.) have shaped history, decimating the human population and changing the way people live (Hays, 2005). Government interventions such as quarantines to contain the spread of contagious diseases are more modern concepts; quarantine was first used in Venice in 1127 (quarantagiorni = forty days) to combat leprosy (Newman, 2012). Historic accounts lay out how authorities tried to fight pandemics but due to a lack of detailed data, very little is known about how these often drastic interventions shaped society, in particular the economic, political, and social attitudes of the population.

Today, the human population is confronted with the outbreak of a new disease. On March 11, 2020, the World Health Organization (WHO)...
classified the coronavirus disease 2019 (COVID-19) as a global pandemic. Many countries implemented social distancing and mobility restrictions to contain the spread of the virus. As a consequence, this pandemic has led to lockdowns of entire regions and countries around the world, and it has affected nearly every aspect of economic, social, and political life. This new pandemic provides an opportunity to study the impact of a severe shock and drastic government interventions on a wide range of attitudes in society.

We use a novel dataset, which captures a “lightning in a bottle” moment. While the pandemic rapidly spread and nationwide lockdowns were implemented, we conducted large-scale surveys in France, Germany, Spain, and the United Kingdom with around 19,500 respondents, whose precise location is recorded in geocodes. This survey allows us to investigate the impact of the COVID-19 induced restrictions, including lockdowns, on socio-economic attitudes as the virus began to spread through these countries and WHO declared a public health emergency of international concern. It is quite clear that such a large shock affects all people. However, we are particularly interested in the differential impact in different types of settlements. Several researchers, politicians, and news commentators have (maybe prematurely) announced an exodus from big cities as the pandemic has partly destroyed the productivity advantages and benefits from social interactions in large agglomerations; for a discussion of the potential mechanisms, see, for instance, Ahlfeldt et al. (2021) or Nathan and Overman (2020) as well as the literature cited there. This would suggest that people living in urban areas and particularly in big cities are affected the most. They may have incurred high debt to finance an apartment or house, which may now be significantly dropping in value. The mark-up on wages in cities may vanish as firms establish ways to maintain high productivity from those working remotely from home. And some popular amenities may vanish when the exodus from cities really takes place. All this suggests that people living in densely populated areas are affected most by the pandemic and the accompanying government policies as their lifestyles and assets are severely threatened. In contrast, people living in rural areas could almost be neutral remote observers. Their lifestyle will hardly be affected, lockdowns are much more bearable where people have access to open countryside and, if an exodus from big cities really occurs and working from home becomes standard, land values in rural areas may even increase. On the other hand, previous literature also argues that residents of rural areas may lack the financial resources to cope with severe crises (Pender et al., 2019). Rural areas also have a heightened exposure to labor market shocks (Thiede and Slack, 2017) and poorer access to healthcare (Berry, 2014). Therefore, it is not clear, a priori, whether urban or rural areas will be more affected by the pandemic.

We classify the respondents’ place of residence by the degree of urbanization in the district (NUTS3 level). Taking the degree of urbanization into account, we examine the impact on perceptions of economic insecurity, to what extent the pandemic has affected the population’s confidence in its institutions (both domestic and international institutions), and the influence on feelings of loneliness. Given our survey is a non-randomized intervention our identification strategy follows several steps. First, given that individuals who participate before and after lockdown may differ from each other, we use a matching approach called coarsened exact matching (CEM; Iacus et al., 2011). Secondly, we adopt a regression discontinuity design (RDD) to test for the immediate (contemporaneous) structural break caused by the lockdown on economic insecurity, political trust, and social inclusion. Additionally, we present a pseudo-event study taking into account our limitations in terms of not having previous year observations. This analysis provides some evidence of the anticipation or duration effects of the lockdown implementation.

Our results highlight the role of the residential environment in understanding the heterogeneous effects of the COVID-19 pandemic. We document that rural areas were hit harder: they exhibit a larger increase in economic insecurity and a larger decrease in trust in domestic institutions. Moreover, our results are especially visible for women and families with children.

In the next section, we provide a discussion of the relevant literature for our analysis. The full literature on social interactions, economic insecurity, and political attitudes, needless to say, is too comprehensive by far to be reviewed in a compact manner. Therefore, we provide a brief definition for each concept and mostly focus on those contributions in the literature that look at the interaction of each of these concepts with large shocks in general and pandemics in particular. Then we introduce our dataset and the empirical strategy. Finally, we present the results and main conclusions.

2. Literature

2.1. Economic insecurity

Previous literature reports a disproportionately large decline in economic security in rural areas, especially in the US (Pender et al., 2019). If residents in rural areas have fewer financial resources, this may make them economically more vulnerable during a pandemic. This hypothesis is supported by Mueller et al. (2021), who shows that the effects of the COVID-19 pandemic on rural populations have been severe, with significant negative impacts on employment, overall life satisfaction, mental health, and economic outlook. By the same token, Altig et al. (2020) examined several measures of economic uncertainty before and during the COVID-19 pandemic and report huge jumps in uncertainty in response to the pandemic. Fetzer et al. (2020), using a dataset on internet searches and representative surveys, found a substantial increase in economic anxiety during and after the arrival of coronavirus. Binder (2020) argues that greater concerns about the Coronavirus are associated with higher inflation expectations and more pessimistic employment expectations. Hanspal et al. (2020) used survey data of more than 8000 US households to provide evidence of the effect of the COVID-19 pandemic on their expectations of spending, debt, labor market activity, and the recovery of their wealth and income. The authors argue that while the stock market crash after the pandemic had a significant effect on planned retirement and working hours, it had a negligible effect on spending. There is also a small number of papers dealing with earlier outbreaks of viral diseases and their impact on economic insecurity. Investigating the social consequences of quarantine during the Ebola outbreak in Liberia, Pellecchia et al. (2015) observe that a mandatory prohibition of movement created serious socio-economic distress. Cava et al. (2005), exploring the experience of quarantine during the severe acute respiratory syndrome (SARS) outbreak in Toronto, document the expression of serious economic insecurity during interviews even though none of the participants in the study reported significant financial hardship due to quarantine: all respondents were compensated for stoppage by their employers or the government. Hawryluck et al. (2004) show that lower income was directly related to increasing symptoms of both post-traumatic stress disorder and depression during the SARS quarantine in Toronto. Brooks et al. (2020) argue that the stronger symptoms of

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1 https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020

2 For simplicity, we interchangeably use the terms lockdowns, social mobility restrictions, and quarantine throughout the paper, even though the measures differed in detail across countries. The measures to implement physical distancing ranged from strict quarantines, which forced people to stay inside their homes, to temporary closures of certain businesses and restrictions on the number of people coming together.
The link between a health shock and political trust was investigated by Blair et al. (2017), who focused on the Ebola epidemic in Liberia in 2014–15. In contrast to our approach, however, they did not analyze how the shock affected trust but rather asked how trust in government affected responses to policy measures. Respondents with low trust in government were less willing to follow the government-mandated policy measures and to take precautions against Ebola. Flückiger et al. (2019) analyzed the same epidemic and show that the increase in political trust was particularly strong in regions highly affected by the virus. This increase was mostly driven by the government’s response rather than by exposure to the disease itself. The detrimental effects of distrust on health is impressively documented by Aban and Wamamaker (2018); the exploitation and mistreatment by the medical profession of adult black men with syphilis from the 1930s to the early 1970s reduced the trust of this group in the US health care system, which in turn reduced significantly their life expectancy. The current COVID-19 pandemic was investigated through an online survey, as in our case, by Daniele et al. (2020) who found a decline in institutional trust. Bargain and Aminjo (2020) examined whether confidence in authorities prior to the crisis affected compliance with lockdown policies, as measured by changes in human mobility. They found that the mobility reduction was larger in European regions with higher levels of political trust.

2.3. Social interaction

Regarding the impact of lockdowns on social interaction, we focus our analysis on the concept of emotional loneliness. de Jong-Gierveld (1987) defines loneliness as a situation that occurs from a lack of quality relationships, which includes “situations in which the number of existing relationships is smaller than is considered desirable or admissible”. One of the consequences of quarantine is a sharp reduction in the number of social interactions, thus increasing the sense of loneliness. Brodeur et al. (2021) looked at the effect of COVID-19 lockdowns on population well-being and observed that people’s mental health may have been severely affected. They found a substantial increase in the search intensity for social interactions. Hossain (2020) surveyed evidence on mental health outcomes of quarantine or isolation for preventing infectious diseases and affirmed higher loneliness during periods of isolation. Participants in a study of Toronto’s large-scale quarantine during the outbreak of SARS in 2003 also reported loneliness as one of the emotional reactions to social distancing (DiGiovanni et al., 2004). For the COVID-19 quarantine, Killigore et al. (2020) documented that the pandemic has increased loneliness among US adults. Orgilés et al. (2020) examined the emotional well-being of Italian and Spanish children aged between 3 and 18 in quarantine; more than 30% of the children reported feelings of loneliness. In a study focusing on the first week of the lockdown period in Spain, Losada-Baltar et al. (2020) found that greater loneliness was expressed by women and by people who devoted more time looking for and processing COVID-19 information. Focusing on the impact of this global pandemic on people’s loneliness in relation to the area which they live (rural vs. urban), Bu et al. (2020a) and Bu et al. (2020b) showed that people living in urban areas in the UK had a higher risk of being lonely and that living in a rural area was a social factor that may have protected against loneliness, both before and during the pandemic. Henning-Smith (2020) argued that stay-home orders particularly affected older adults in rural areas as they often faced challenges connecting online.

3. Data

3.1. Data collection and sample

We have conducted large-scale surveys in four European countries: France, Germany, Spain, and the United Kingdom. The survey was designed and programmed by the authors via Qualtrics, and it was administered between March 3 and March 30, 2020 in all four countries.
by the company Respondi (https://www.respondi.com/EN/), which has access to panels of representative samples of respondents to whom they send out survey links by email. Respondents were paid only if they fully completed the survey. The average time spent completing the survey was 30 min. Our survey was not designed to capture the COVID-19 effect, but was planned to be run before the pandemic was declared. The sample sizes are 5285 for Germany (DE), 4825 for Spain (ES), 4939 for France (FR), and 4395 for the United Kingdom (UK), a total of 19,444 observations. The survey data also contains the geocodes (longitude and latitude) of the respondents. Using Qgis and the Eurostat shape file, (https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nutsEurostat Shapefile), we matched the geocodes with the NUTS3 classification. Hence, each respondent was assigned his/her location on the district level.

As a response to the COVID-19 pandemic, the four national governments restricted basic freedom rights during the administration of this survey. Lockdowns were imposed – to different degrees – on March 14 in Spain, on March 17 in France, and on March 22 in Germany, and on March 24 in the United Kingdom. The last day of the survey in Germany and the United Kingdom was March 26 (see Table 1). Therefore, the data from these two countries should be interpreted with caution for the period after the lockdowns due to the relatively few number of days.

3.2. The survey structure

The survey has four components: (1) socio-demographic characteristics, (2) economic insecurity, (3) political attitudes, and (4) social inclusion. The relevant questions from the English version of the survey are presented in Appendix A.

In the first block of questions, respondents were asked about socio-demographic characteristics such as gender, age, marital status, number of children, household income level, employment status, education level, and political orientation. In the second block, we explored the participants’ perceptions of economic insecurity using a question from the European Social Survey (ESS), Round 8, 2016/2017. The particular question was as follows: Which of the descriptions comes closest to how you feel about your household’s income nowadays? The answer options were 1 (finding it very difficult on present income), 2 (finding it difficult on present income), 3 (coping on present income), or 4 (living comfortably on present income), thus a higher score means feelings of greater economic security. Following the literature (Bossert and D’Ambrosio, 2011), we also included information about job insecurity. The specific question was: The country will face a situation of ever increasing job insecurity. The answer options ranged from 0 (Completely disagree) to 10 (Completely agree) with higher scores showing more perceived economic insecurity.

In the third block of questions, we attempted to elicit political attitudes. In particular, we were interested in respondents’ trust in domestic and international institutions. The trust dimension was captured by the following question: Please indicate on a scale of 0-10 how much you personally trust each of these institutions (0= Do not trust at all; 10= Complete trust): National parliament / The legal system / The police / Politicians / Political parties / The European Parliament / The United Nations. Here we followed Algan et al. (2017) and the European Social Survey. Many papers basically use these types of questions though sometimes with different scales. For instance, the Afrobarometer (Flückiger et al., 2019) and the Gallup poll (Stevenson and Wolters, 2011) use a scale from 0 to 3, the Eurobarometer (Drakos et al., 2019) only employs a binary variable. For trust in domestic institutions, we used information from the first five institutions. Trust in international institutions was measured by the questions regarding the EU and the UN. Higher scores show greater trust in institutions.

In the last block, participants were asked about their subjective evaluations of loneliness. Regarding loneliness, we used the De Jong-Gierveld Loneliness Scale. This scale has been proved as a reliable and valid measurement instrument for overall, emotional, and social loneliness suitable for large surveys (de Jong-Gierveld and Tilburg, 2006). For this survey, we focused on three statements regarding emotional

5 We describe the final sample in the Online Appendix, section 1. We also show the characteristics of the whole sample relative to the population in each country and distribution of answers through the whole period of interviews.

6 The ESS systematically measures the attitudes, beliefs, and behavior patterns of diverse populations in more than thirty European nations.

7 We reverted the original scale so that a higher score means feelings of greater economic insecurity.

8 The trust in the legal system data was not available for Germany.
loneliness. Participants had to indicate to what extent they agree with the following statements: (1) I experience a general sense of emptiness; (2) I miss having people around me, and (3) I often feel rejected. Higher scores show a greater feeling of loneliness. (0 = Completely disagree; 10 = Completely agree).

To aggregate the responses to all questions within the corresponding category (economic insecurity, trust in domestic institutions, etc.), we built an indicator \( ic \) on individual \( i \) in country \( c \), using Principal Component Analysis (PCA). The PCA idea is simple: one reduces the dimensionality of a concept, while preserving as much variability (i.e. statistical information) as possible but at the same time minimizing information loss. This means that “preserving as much variability as possible” translates into finding new variables that are linear functions of those in the original data-set, that successively maximize variance, and that are uncorrelated with each other. Finding such new variables, the principal components, reduces to solving an eigenvalue/eigenvector problem, and the new variables are defined by the dataset at hand, not a priori, hence making PCA an adaptive data analysis technique. Besides, it provides a method to select a subset of components that explain most of the variation (Kaiser criterion or latent root criterion). In our case, we employed the Kaiser-Meyer-Olkin criterion to measure the sampling adequacy. In our analysis, the criterion is fulfilled in all cases (KMO statistics are above 0.5), and therefore the use of PCA is justified. Main descriptive statistics that compare pre- and post-lockdown values for each of the geographical entities for the four indicators are reported in Table 2. Note that the new indicators are continuous variables centered at zero with standard deviations equal to one, as the original variables were standardized. The interpretation is similar to the original variables, the larger the indicator the greater the perception in each dimension (economic insecurity, trust, and loneliness).

The values of all indices increase in the post-lockdown period compared to the time before the lockdowns (except for trust in international institutions). The indices for economic insecurity, loneliness and trust in domestic institutions are higher after the lockdown. And this pattern is valid for each geographic entity. For all indices, the ranking in the pre-lockdown period assessment (unconditional mean) by degree of urbanization remains after the lockdown. For example, in the case of economic insecurity the assessment before lockdown was highest in rural areas and remains so after lockdown. However, given that these are unconditional means, the findings do not properly describe the effect of the degree of urbanization.

In terms of socio-economic characteristics, we included gender as a dummy, which takes value 1 for women. We modeled age with three dummies: less than forty years old (Young), between forty and sixty-five years old (Middle), and more than sixty-five years old (Old). In terms of monthly net household income, we considered three dummies: Low, Middle, and High. The thresholds for defining the different groups varied by country.\(^{10}\) We also considered the household structure by including a dummy to capture the fact of having children (Children) and being married (Married). Educational attainment was represented through a set of dummies: Primary, Secondary, and Tertiary. Labor market status was also modelled by a set of dummies for Working, Self-employed, Unemployed, and Studying. There was a specific question about where a respondent placed herself/himself in terms of political orientation (0 = Left; 10 = Right). We built a dummy for extreme left (Ext_left) if they reported values from 0 to 2 and for extreme right (Ext_right) if they answered values from 8 to 10. Finally, we controlled for the degree of urbanization. We employed the official Eurostat classification, which distinguishes between predominantly urban areas, intermediate areas, and predominantly rural areas. Based on the population shares, it classifies NUTS3 regions into cities (densely populated areas), towns and suburbs (intermediate density areas), and rural areas ( thinly populated areas). The main descriptive statistics of our sample are reported in Table 3.

### 4. Identification strategy

The gold standard for the evaluation of the COVID-19 effect is the randomized controlled trial (RCT), but observational studies are an alternative when RCTs are not feasible. A primary challenge to evaluating outcomes of non-randomized interventions is self-selection bias. Individuals who choose to participate after lockdown may differ from individuals who choose to participate before. Observational studies attempt to approximate the design of RCTs as much as possible (Rubin et al., 2008; Rosenbaum et al., 2009). The most common matching approach is to match on a propensity score (Rosenbaum and Rubin, 1983). However, some researchers have more recently advocated coarsened exact matching (CEM; Iacus et al., 2011). The advantages of CEM relative to propensity matching include the fact that increasing the balance on one variable cannot increase imbalance on another (this can happen in propensity matching), ease of implementation, less sensitivity to measurement error, and greater computational efficiency. In CEM, variables are “coarsened” by categorizing prior to creating the strata; then individuals are placed into the appropriate stratum (Iacus et al., 2011). Strata including at least one individual in each group (pre-lockdown and lockdown period) are retained in the analysis, while all other

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10 For France, using OECD data ([https://stats.oecd.org/](https://stats.oecd.org/)), the thresholds are: less than 1500€, 1500€ to 3000€, more than 3000€. For Germany, using Statistisches Bundesamt ([https://www.destatis.de/DE/Home/inhalt.html](https://www.destatis.de/DE/Home/inhalt.html)), thresholds are defined as: less than 1500€, 1500€ to 4500€, more than 4500€. For Spain, using National Statistics Institute ([https://www.ine.es/](https://www.ine.es/)), thresholds are recorded as: less than 1000€, 1000€ to 3000€, more than 3000€. For the United Kingdom, using HM Revenue and Customs ([https://www.gov.uk/search/research-and-statistics](https://www.gov.uk/search/research-and-statistics)), thresholds are defined in weekly net household incomes: less than £ 400; £ 400 to £ 1000; more than £ 1000.

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\(^{9}\) The main descriptive statistics on the principal components analysis are shown in the Online Appendix, Section 2.
strata (and the individuals in them) are excluded. A weight is created for each unit in the retained strata.

The literature mainly suggests three different methodologies to identify the causal effect of an intervention (lockdown): (i) a difference-in-differences (DiD) approach; (ii) a regression discontinuity design (RDD) with or without difference-in-differences (RDD-DiD), and (iii) an event study. Difference-in-differences (DiD) has become one of the most popular research designs used to evaluate causal effects of policy interventions. In its canonical format, there are two time periods and two groups: in the first period no one is treated, and in the second period some units are treated (the treated group), and some units are not (the comparison group). A similar data structure is required when considering the event study methodology as it requires at least two periods. The lack of a panel structure in the data set as well as all countries imposing lockdowns at some point makes the DiD methodology difficult to implement.

Thus, once we matched the data, we adopted a regression discontinuity design (RDD) to test for the immediate (contemporaneous) structural break caused by the lockdown on economic insecurity, political trust, and social inclusion. The goal was to obtain estimates for the immediate effect of the actual break and also of the few days around each lockdown implementation, rather than compare all pre-announcement observations with all post-announcement observations, which is what the DiD results would provide (Brodeur et al., 2021). The lockdown dates in our analysis are the dates at which the lockdowns became effective. Some individual perceptions may have already been affected when the policy was announced to the public. However, as described in the previous section, the gap between announcement and implementation was very short.

Following recent literature, for example Brodeur et al. (2021), we estimate the regression model for each of the indicators $I$ of economic insecurity, political trust, and social loneliness as follows:

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\[ \text{Fig. 1. Average daily level of indicators before and after the lockdown. Note: The vertical axis shows the average level of indices (values reported in Table 3) in days before (negative values) and after (positive values) the lockdown. Dots correspond to the raw averages by bins of one day. Red solid vertical lines represent the date when 10 deaths were reached; dashed red lines represent the lockdown. DE (Germany), ES (Spain), FR (France) and UK (United Kingdom).} \]

\[ \text{11 Many DiD empirical applications, however, deviate from the canonical DiD setup and have more than two time periods and variation in treatment timing. Callaway and Pedro H.C (2021) provides a unified framework for average treatment effects in DiD setups with multiple time periods, variation in treatment timing, and when the parallel trends assumption holds potentially only after conditioning on observed covariates.} \]

\[ \text{12 We have added some additional analysis in Online Appendix, section 2, regarding the unconditional structural break. We also include some sensitivity analysis.} \]
The effect of lockdown (RDD estimates).

|                          | Economic Insecurity | Trust Dom. Institutions | Trust Int. Institutions | Loneliness |
|--------------------------|----------------------|-------------------------|-------------------------|------------|
| **Lockdown**             | 0.139 ** *           | 0.190 *                 | 0.023                   | 0.095      |
|                          | (0.043)              | (0.050)                 | (0.080)                 | (0.084)    |
| **Before**               | 0.005                | 0.008                   | 0.009                   | 0.011      |
|                          | (0.005)              | (0.005)                 | (0.010)                 | (0.010)    |
| **After**                | -0.002               | 0.002                   | -0.013                  | -0.018     |
|                          | (0.007)              | (0.008)                 | (0.015)                 | (0.010)    |
| **Intermediate regions** | 0.006                | -0.000                  | -0.085 ** *             | -0.049     |
|                          | (0.020)              | (0.060)                 | (0.038)                 | (0.114)    |
| Predominantly rural regions | 0.057                | -0.152                  | -0.168 *               | 0.056      |
|                          | (0.038)              | (0.114)                 | (0.059)                 | (0.215)    |
| **Lockdown** *Intermediate regions** | 0.021                | -0.172                  | -0.061                  | 0.104      |
|                          | (0.081)              | (0.153)                 | (0.112)                 | (0.114)    |
| **Lockdown** *Predominantly rural regions** | 0.359 *              | -0.680 *               | -0.390 +               | 0.359 +    |
|                          | (0.151)              | (0.287)                 | (0.210)                 | (0.213)    |
| **Before** *Intermediate regions** | 0.000                | -0.003                  | -0.015 *               | 0.002      |
|                          | (0.005)              | (0.009)                 | (0.007)                 | (0.007)    |
| Before *Predominantly rural regions** | -0.016 +             | 0.017                   | 0.013                   | -0.015     |
|                          | (0.009)              | (0.017)                 | (0.013)                 | (0.013)    |
| **After** *Intermediate regions** | -0.000               | 0.022                   | 0.026 *               | -0.011     |
|                          | (0.009)              | (0.017)                 | (0.012)                 | (0.013)    |
| After *Predominantly rural regions** | -0.021               | 0.085 *               | 0.045 +               | -0.027     |
|                          | (0.017)              | (0.023)                 | (0.024)                 | (0.025)    |

Note: Standard errors are clustered at the day level. *p < 0.1, **p < 0.05, ***p < 0.01, ****p < 0.001. We include socio-demographic characteristics regarding gender, age, income, presence of children, marital status, education level, working status and political orientation (see Table 3) as well as country- and day-fixed effects. * Before corresponds to variable $f(D_{ic})(1 - Lockdown_{ic})$ and After to $f(D_{ic})Lockdown_{ic}$ in Eq. (1).

\[ I_{ic} = \beta_0 + \beta_1 Lockdown_{ic} + \beta_2 f(D_{ic}) Lockdown_{ic} + \beta_3 f(D_{ic})(1 - Lockdown_{ic}) + \beta_4 Intermediate_{ic} + \beta_5 Rural_{ic} + \beta_6 X_{ic} + \mu_i + \rho_c + \epsilon_{ic} \]  

(1)

**Lockdown** is a dummy that takes value 1 in the days after the stay-at-home order was implemented and 0 beforehand. The running variable $D_{ic}$ is defined as the distance in days from the implementation of the stay-at-home order; it is negative for the days before and positive for the days after, while the date of the actual or counterfactual implementation is set as day 0 (and dropped from the empirical model, as is standard). $f\left(D_{ic}\right)$ is a polynomial function of the distance in days from the lockdown implementation interacted with the lockdown variable $Lockdown_{ic}$, to allow for different effects on either side of the cut-off. Our regression regarding the whole set of indicators. Our parameters of interest are $\beta_1$, which captures the causal effect of the event on economic, political, and social indicators, and $\beta_2$ and $\beta_3$, which show us the immediate effect in the few days around the announcement.

We will also investigate whether those effects vary by degree of urbanization, adding the interactions between the degree of urbanization (predominantly urban areas, intermediate areas, and predominantly rural areas) with our variables of interest.

\[ I_{ic} = \beta_0 + \beta_4 Lockdown_{ic} + \beta_1 Lockdown_{ic} * Intermediate_{ic} + \beta_5 Lockdown_{ic} * Rural_{ic} + \beta_6 f(D_{ic}) Lockdown_{ic} + \beta_3 f(D_{ic})(1 - Lockdown_{ic}) * Intermediate_{ic} + \beta_7 f(D_{ic})(1 - Lockdown_{ic}) * Rural_{ic} + \beta_2 Intermediate_{ic} + \beta_8 Rural_{ic} + \beta_6 X_{ic} + \mu_i + \rho_c + \epsilon_{ic} \]  

(2)

In this way, the original parameters, for example $\beta_1$, which captures the causal effect of the lockdown on economic, political, and social indicators, are disentangled from the effect on urban areas $\beta_{10}$, intermediate areas $\beta_{11}$, and rural areas $\beta_{12}$, respectively.

5. Results

In this section, we test the possible structural break caused by the lockdown implementation as well as the immediate effect in the few days around the lockdown implementation. We put particular emphasis
Table 5
The effect of lockdown (RDD estimates by group).

| Economic Insecurity                      | All          | DE | ES | FR | UK | Male | Female | No child | Child | Young | Old | Low Inc. | High Inc. | Work | Unemp. |
|------------------------------------------|--------------|----|----|----|----|------|--------|---------|-------|-------|-----|---------|-----------|------|--------|
| Lockdown 0.10 ** 0.385 ** ** 0.011 0.06 | 0.060 **     | 0.136 ** | 0.078 | 0.103 | 0.142 | 0.018 | 0.152 | -0.108 | 0.137 ** | -0.235 |
| Before 0.008 -0.007 0.001 -0.016 0.010 | 0.014 | 0.004 | 0.006 | 0.009 | -0.014 | 0.049 ** ** 0.006 | -0.002 | -0.001 | 0.041 |
| After 0.002 -0.077 ** 0.016 0.037 | 0.071 | 0.011 | -0.006 | 0.004 | 0.000 | 0.014 | -0.022 | -0.006 | -0.001 | -0.002 |
| Intermediate regions -0.000 -0.043 | 0.168 | 0.000 | 0.009 | 0.085 | -0.053 | -0.014 | -0.011 | 0.054 | -0.129 | 0.152 | -0.247 | 0.028 | -0.159 |
| Lockdown#Predominantly rural regions -0.152 | 0.014 | -0.833 ** 0.114 | 0.396 | -0.122 | -0.178 | 0.043 | -0.626 ** 0.281 | -0.267 | 0.133 | -0.085 | -0.266 + 0.136 |
| Lockdown#Intermediate regions 0.021 | -0.122 | -0.163 | 0.386 | 0.046 | -0.026 | 0.038 | 0.079 | -0.001 | 0.100 | 0.220 | -0.216 | 0.592 ** * -0.054 | 0.287 |
| Lockdown#Predominantly rural regions 0.359 ** | -0.061 | 1.692 * 0.198 | 0.000 | 0.247 | 0.450 ** 0.231 | 0.431 * 0.165 | 0.241 | 0.281 | 0.183 | 0.420 + 0.175 |
| Trust in Domestic Institutions           |              |    |    |    |    |      |        |         |       |       |     |         |           |      |        |
| Lockdown 0.095 0.087 0.557 * -0.323 | 0.020 | 0.105 | 0.130 | 0.033 | 0.140 | 0.148 | 0.201 | -0.003 | 0.396 | 0.169 | -0.195 |
| Before 0.000 -0.003 0.025 | 0.003 | 0.001 | 0.006 | -0.004 | -0.001 | -0.000 | 0.003 | -0.012 | 0.017 | -0.018 | 0.003 |
| After 0.005 (0.009) (0.023) (0.016) | 0.010 | (0.007) | (0.006) | (0.008) | (0.006) | (0.009) | (0.010) | (0.011) | (0.015) | (0.016) | (0.017) |
| Intermediate regions -0.016 -0.005 | -0.033 | 0.099 | 0.011 | -0.009 | -0.022 + 0.009 | -0.021 + 0.008 | -0.017 | -0.001 | -0.001 | -0.022 + 0.031 |
| After 0.009 | 0.015 | 0.061 | (0.018) | (0.025) | 0.015 | (0.012) | (0.018) | 0.010 | (0.019) | (0.021) | (0.020) | (0.026) | (0.011) | (0.047) |
| After 0.000 0.055 | 0.000 | -0.058 * | -0.042 | -0.002 | 0.001 | -0.004 | 0.002 | 0.004 | 0.018 | 0.009 | -0.046 + 0.000 | 0.011 |
| After 0.009 -0.049 | -0.118 | -0.334 | 0.161 | -0.011 | -0.027 | -0.039 | -0.014 | -0.014 | -0.042 | -0.055 | -0.020 | 0.015 | -0.007 |
| After 0.017 | 0.077 | (0.085) | (0.033) | (0.291) | 0.026 | (0.023) | (0.030) | (0.021) | (0.036) | (0.039) | (0.038) | (0.047) | (0.023) | (0.075) |
| Trust in International Institutions      |              |    |    |    |    |      |        |         |       |       |     |         |           |      |        |
| Lockdown 0.095 | 0.001 | 0.004 | 0.007 | -0.009 | -0.015 | -0.021 | -0.004 | 0.008 | -0.008 | 0.004 | -0.013 | 0.001 |
| Before 0.000 -0.016 | -0.036 | 0.020 | 0.001 | -0.013 | -0.001 | 0.025 + 0.002 | 0.017 | 0.006 | 0.004 | 0.000 | 0.007 |
| After 0.009 | 0.017 | 0.044 | 0.032 | 0.011 | 0.014 | 0.012 | 0.017 | 0.019 | 0.041 | 0.051 | 0.004 | 0.038 | 0.019 | 0.017 |
| After 0.007 | 0.022 | 0.046 | 0.020 | -0.002 | 0.125 | 0.011 | 0.028 | 0.045 | 0.012 | 0.022 | 0.067 | -0.005 | 0.040 | 0.031 | 0.040 |
| After 0.007 | 0.022 | 0.046 | 0.020 | -0.002 | 0.125 | 0.011 | 0.028 | 0.045 | 0.012 | 0.022 | 0.067 | -0.005 | 0.040 | 0.031 | 0.040 |
| After 0.007 | 0.022 | 0.046 | 0.020 | -0.002 | 0.125 | 0.011 | 0.028 | 0.045 | 0.012 | 0.022 | 0.067 | -0.005 | 0.040 | 0.031 | 0.040 |
| Trust in International Institutions      |              |    |    |    |    |      |        |         |       |       |     |         |           |      |        |
| Lockdown 0.041 | -0.017 | 0.266 | -0.203 | -0.087 | 0.011 | 0.081 | -0.071 | 0.091 | -0.045 | 0.008 | 0.037 | 0.376 + 0.095 | -0.312 |
| Before 0.001 -0.004 | -0.056 * | 0.016 | 0.018 | 0.001 | -0.006 | -0.005 | 0.003 | 0.008 | -0.012 | 0.030 | -0.007 | 0.018 |
| After 0.007 | 0.030 ** | -0.009 | 0.045 | 0.028 | 0.013 | -0.034 | -0.038 ** | -0.009 | -0.043 ** | -0.027 | -0.041 | -0.012 | -0.055 + 0.002 ** | -0.019 |

(continued on next page)
Table 5 (continued)

| Economic Insecurity                  | All          | DE          | ES          | FR          | UK          | Male        | Female      | No child    | Child       | Young       | Old         | Low Inc.    | High Inc.   | Work        | Unemp. |
|--------------------------------------|--------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|------------|--------|
| Intermediate regions                 |             | (0.011)     | (0.050)     | (0.024)     | (0.034)     | (0.070)     | (0.018)     | (0.014)     | (0.018)     | (0.014)     | (0.020)     | (0.020)     | (0.021)     | (0.031)    | (0.015) |
| Predominantly rural regions          | 0.004        | (0.283)     | (0.283)     | (0.250)     | (0.250)     | (0.209)     | (0.209)     | (0.209)     | (0.153)     | (0.153)     | (0.145)     | (0.145)     | (0.145)     | (0.145)    | (0.044) |
| Lockdown#Intermediate regions        | -0.001       | (0.026)     | (0.073)     | (0.005)     | (0.016)     | 0.046       | 0.016       | 0.006       | 0.016       | 0.006       | 0.006       | 0.016       | 0.006       | 0.006      | 0.006   |
| Lockdown#Predominantly rural regions | -0.390 +     | 0.354       | -0.019      | 0.005       | -0.015      | -0.015      | -0.015      | -0.015      | -0.015      | -0.015      | -0.015      | -0.015      | -0.015      | -0.015     | -0.015   |
| Loneliness                           |              |             |             |             |             |             |             |             |             |             |             |             |             |             |         |
| Lockdown                             | 0.057        | 0.004       | 0.005       | -0.011      | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014     | 0.014   |
| After                                |              | (0.024)     | (0.046)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)   | (0.037) |
| Loneliness                           |              |             |             |             |             |             |             |             |             |             |             |             |             |             |         |
| Lockdown                             | 0.057        | 0.004       | 0.005       | -0.011      | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014       | 0.014     | 0.014   |
| After                                |              | (0.024)     | (0.046)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)     | (0.037)   | (0.037) |

Note: Standard errors are clustered at the day level. \( \ast \ p < 0.1, \ast \ast \ p < 0.05, \ast \ast \ast \ p < 0.01, \ast \ast \ast \ast \ p < 0.001. \) We include socio-demographic characteristics regarding gender, age, income, presence of children, marital status, education level, working status and political orientation (see Table 3) as well as country- and day-fixed effects.
on the differential impact in urban and rural environments. Before proceeding with the main results, we comment on CEM and the indicators’ joint estimation tests. First, we find that the percentage of matched individuals in both groups is close to one hundred and that the multivariate distance is $1.272e^{-14}$. Note that the lower the multivariate distance the more balance between treated and control with respect to the full joint distribution, including all interactions, of the covariates. Perfect global balance (up to coarsening) is indicated by $L_1 = 0$, and larger values indicate a larger imbalance between the groups, with a maximum of $L_1 = 1$, which indicates complete separation.

In terms of correlation among the idiosyncratic error terms, we find that the t-statistic for the Breusch-Pagan test of independence for the whole sample is 32,882.13, distributed as a chi-squared with 28 degrees of freedom; therefore, the p-value is 0.0000. The null hypothesis of independence of equations is rejected; thus we must estimate all indicators simultaneously.

5.1. Main results

We begin our analysis by comparing the raw data indices pre- and post-lockdown in 2020. Fig. 1 plots daily information for indices. Sometimes there are “jumps” at the lockdown. There are also anticipation or post-lockdown effects. We also observe that some of the jumps do not consolidate in the days after the lockdown.

In order to capture the effect caused by the lockdowns, we report now the estimation results from Equations 1 and 2, described in the previous section. To disentangle the differential effect by degree of urbanization, we do not run separate regressions, but we include the interaction of the residential environment with our variables of interest. We also run separate regressions by socio-economic characteristics so that we can have a bird-eye view of the groups of individuals who may have responded differently to the lockdown. We first present estimation results for the whole sample in Table 4, before we turn to the separate regressions for countries and socio-economic groups in Table 5.

The first columns in each group of regressions show how the variables of interest vary across regions and during the lockdown (Table 4). We document that the lockdown has increased economic insecurity in all regions. Moreover, trust in institutions is higher in urban areas in general. Adding the interaction terms show that rural regions experienced a deterioration in all dimensions of attitudes (Table 4, Lockdown#Predominantly rural regions). Economic insecurity was higher after the lockdowns were implemented, but this effect was significantly more pronounced in rural regions. This perception of an economic impact in rural areas is consistent with the findings of Mueller et al. (2021) and with the recent literature analyzing expectations and economic anxiety during a pandemic (Altig et al., 2020; Bartik et al., 2020; Binder, 2020; Fetzer et al., 2020; Hanspal et al., 2020). Political trust in domestic and international institutions was not affected in urban and intermediate regions but again there was a significant decline in trust among people in rural areas. The significant positive interaction with the time elapsed after the lockdown implementation.

13 We have considered in the CEM analysis strata built on gender, age, education, income, employment status, and density of area of living.

14 A general decrease in political trust was found by Daniele et al. (2020), who also use a survey during the COVID-19 pandemic.
After Predominantly rural regions) suggests that there was a slight recovery of trust in rural regions. Somewhat surprising is the significant increase in social loneliness in rural regions. Respondents in urban and intermediate regions report no increased feelings of loneliness due to the lockdown; one might expect the urban population in particular to be affected by lockdowns as the typical personal interaction in urban environments – meeting in pubs, jointly visiting cultural events. – is no longer viable. However, no such effect is detectable. Instead, it is the rural population that reports an increased feeling of loneliness in the lockdown period.

5.2. Heterogeneous effects

Next, we zoom in and take a closer look at the disaggregated results for the single countries and various socio-demographic groups. The pattern that emerges in the aggregate is not uniform across countries (Table 5). Regarding economic insecurity, Germany and the UK show a lockdown effect (with opposite signs) for the reference group; hence, urban areas saw an increase in economic insecurity in Germany and a decrease in the UK. In Spain, people in the rural areas experienced an increase in economic insecurity after the implementation of the lockdown. In France, economic insecurity in intermediate regions decreased in the days after the lockdown. Turning to trust in domestic institutions, we see that the significant negative interaction between lockdown and rural environments holds for France and Spain, which exhibits a recovery of trust in rural areas in the days after the lockdown. Germany’s rural regions even show a significant increase in trust after the lockdown. Finally, the increase in social loneliness in rural regions is significant for the UK but not the three other countries. Hence, different countries drive the result for rural regions in the different dimensions. The lockdown drives up economic insecurity in Spanish rural regions, decreases trust in Spanish and French rural environments, and enhances loneliness in the British countryside.

When we analyze the respondents according to their socio-demographic groups separately, some interesting patterns emerge. For instance, trust in political institutions decreased among women in rural regions after the lockdown. In contrast, economic insecurity increased after the lockdown for women in both rural and in urban areas. Families with children show exactly the same pattern. Concerning the older population, it is again the respondents in rural areas who lost trust in domestic institutions after the lockdown. In addition, the older population in urban areas experienced a reduced loneliness after the implementation of the lockdown. Among high-income households, it was those in the intermediate regions who saw the strongest increase in economic insecurity after the lockdown. Among low-income households, there was a pronounced increase in loneliness in the rural regions after the lockdown.

In a nutshell, we find that the degree of urbanization plays a crucial role in disentangling the impact of the pandemic on individuals’ socio-economic attitudes. It is the rural areas where the lockdown increased economic insecurity as well as social loneliness and decreased trust in political institutions. These effects vary by country. Spain’s rural regions particularly suffered in the economic and political dimension, whereas the British countryside sees a pronounced hike in loneliness.

Finally, it is worth highlighting that although there are heterogeneous effects by socio-economic groups, there are some groups in rural and intermediate areas, namely women, households with children, and working people, who seem particularly sensitive to the pandemic.

5.3. Pseudo-event approach

Finally, we present an analysis similar to an event study, but taking into account our limitations in terms of not having previous year observations. This analysis provides some evidence of the anticipation or

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Fig. 3. Duration of the effects of the lockdown (Predominantly urban areas). The vertical axis shows pseudo-event-study estimates using Equation 3. The seventh 3-day group before the lockdown (21–19 days before, k = −7) is the reference period. The models include dummies for each week and day of the week. CEM weights are applied. Robust standard errors are plotted.
Fig. 4. Duration of the effects of the lockdown (Intermediate areas). The vertical axis shows pseudo-event-study estimates using Equation 3. The seventh 3-day group before the lockdown (21–19 days before, \( k = -7 \)) is the reference period. The models include dummies for each week and day of the week. CEM weights are applied. Robust standard errors are plotted.

Fig. 5. Duration of the effects of the lockdown (Predominantly rural areas). The vertical axis shows pseudo-event-study estimates using Equation 3. The seventh 3-day group before the lockdown (21–19 days before, \( k = -7 \)) is the reference period. The models include dummies for each week and day of the week. CEM weights are applied. Robust standard errors are plotted.
duration effects of the lockdown implementation.

For the pseudo-event study, we define the 3-day groups (seven groups of three days prior to the lockdown and five groups of three days after the implementation). We set the day of the intervention to 0. The seventh 3-day group before the intervention (k = −7, that is 21–19 days before) is the group of reference. Formally, we estimate the equivalent to the event study for our case:

\[ I_n = \sum_{k=-6}^{k=5} \beta_k \text{Lockdown}_k + \gamma \mathbf{X}_n + \mu_i + \rho_u + \epsilon_n. \] (3)

For example, when k = 2, \( \beta_2 \) informs us of the effect of a lockdown six to four days after its implementation in comparison to 21–19 days before (k = −7). The same number of fixed effects and controls as in Equations (1) are included. We estimate one equation for each of the urban/rural types (predominantly urban regions, intermediate regions, and predominantly rural regions). The pseudo-event study depicted in Fig. 2 shows that economic insecurity continued to be higher throughout the lockdown period,16

By degree of urbanization (Figs. 3–5), we find effects consistent with those obtained previously. In predominantly urban areas, the trends are weaker. For example, the increase in economic insecurity occurs six days before the lockdown announcement before dropping back six days after. In rural areas, the effect of increased economic insecurity persists longer.17

6. Conclusion

Our large-scale survey provides some insights into how the shock of a global pandemic and pandemic-induced lockdowns affected residents of rural and urban areas in the dimensions of economic, social, and political attitudes. This paper contributes to the scarce literature examining the impact of the pandemic based on the degree of urbanization. As did Mueller et al. (2021) for the Western US, we find that, in Europe, the COVID-19 pandemic hit rural areas stronger than urban areas. In particular, we find that, compared to urban areas, in rural areas the lockdown led to higher levels of economic insecurity and to a decrease in trust in domestic institutions. This is somewhat surprising as during the study period COVID-19 lockdowns were supposed to be less severe in rural than in urban areas. Based on our survey, we can only speculate on what drives the difference in responses. For instance, it might be the case that rural respondents already anticipate at the dawn of the pandemic a larger personal impact due to their greater economic vulnerability (Pender et al., 2019; Mueller et al., 2021). We control for household incomes but respondents might be worried about the vulnerability of their neighborhood. Also rural areas tend to have a heightened exposure to labor market shocks (Thiede and Slack, 2017) so that respondents in rural areas may fear lengthy recovery processes with long-term unemployment and stressful structural change. Finally, it could be urban-rural differences in the healthcare system that drive the different responses; rural areas tend to have poorer access to healthcare (Berry, 2014). Identifying the individual drivers of attitudinal changes in rural areas would require in-depth personal interviews with respondents. We also have to keep in mind that we only capture the first days of the lockdown. Hence, we only see the immediate response to the policy measures and not the mid- and long-term hardships of the pandemic.

We detect an increase in trust in both domestic (in rural areas) and international institutions (in rural and intermediate areas) in the days after the lockdown. In addition to the aggregate results, we identify some heterogeneity in the way the shock dissipated: we report significant changes of attitudes in rural and intermediate areas for women and households with children.

Previous studies have already shown that socio-economic perceptions may have significant policy consequences (Alesina et al., 2018). Our study adds two more layers to this result: first and foremost, we show that the global pandemic has decreased trust in domestic institutions. Moreover, we show that this effect is asymmetric and more pronounced in rural areas.

According to the United Nations, “[t]rust is integral to the functioning of any society. Trust in each other, in our public institutions and in our leaders are all essential ingredients for social and economic progress, allowing people to cooperate with and express solidarity for one another”.18 The documented decrease in trust in domestic institutions may even threaten democracy in the future. By highlighting the areas and groups where the above-stated effect is larger in magnitude, we provide a road-map for policymakers to combat extreme political views, increasing public discontent, protests, and in some cases violent conflict.

Future research will have to show whether some of the identified impacts are also persistent in the long run. Unfortunately, our data set does not allow creating a true panel structure. However, merging our data with previous and future surveys containing the same set of questions could provide some insights into the long-run effects via matching procedures – beyond the short- and medium-term effects identified in this paper. One should also keep in mind the usual shortcomings of large-scale surveys, especially regarding the variables that deal with emotions. Nevertheless, our results shed light on challenges that policymakers will face in reconstructing the economic and political landscape in the post-pandemic years to come.

CRediT authorship contribution statement

K. Peren Arin: Conceptualization, Methodology, Writing. Juan A. Lacomba: Conceptualization, Methodology, Writing. Francisco Lagos: Conceptualization, Methodology, Writing. Ana I. Moro-Egido: Methodology, Formal analysis, Writing. Marcel Thum: Conceptualization, Methodology, Writing.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ehbi.2022.101119.

References

Adams-Prassl, Abigail, Boneva, Teodora, Rauh, Christopher, Golin, Marta, 2020. Inequality in the impact of the Coronavirus shock: Evidence from real time surveys. IZA Discuss. 13183.
Abitbol, Eric, 2015. Trust and the economic performance of the US states. J. Econ. Perspect. 29, 133–158.
Alesina, Alberto, Arin, K. Peren, Barro, Robert J., 2017. The impact of trust and institutions on economic growth. J. Eur. Econ. Assoc. 15, 1198–1230.
Alesina, Alberto, Capalbo, Ignazio, Chirinko, Robert, 2018. Trust and economic performance in the United States. J. Public Econ. 161, 91–108.
Alesina, Alberto, Dinello, Adam, 2019. Inequality, trust and growth. J. Econ. Perspect. 33, 107–128.
Alesina, Alberto, Glaeser, Edward L., 2004. What explains the cross-country level of trust? Q. J. Econ. 119, 165–194.
Alesina, Alberto, Glaeser, Edward L., 2018. Inequality and the cost of government. NBER Working Paper No. 24945.
Alesina, Alberto, Peri, Giovanni, 2014. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
Alesina, Alberto, Peri, Giovanni, 2015. Political shocks and economic growth. J. Public Econ. 111, 169–181.
