Apuntes 91, 5-43
ISSN: 0252-1865
eISSN: 2223-1757
doi: 10.21678/apuntes.91.1500

Article received on February 15, 2021
Article approved for publication on January 24, 2022

Determinants of the evolution in the number of COVID-19 cases and deaths in Peru: Mobility, geography, and economic development

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Abstract. This research seeks to contribute to the literature on the determinants of the evolution in the number of COVID-19 cases and deaths in Peru; specifically, the role of mobility of people, geography, and economic development. To do so, we use random-effects Poisson regressions and data from four groups of variables at the district level: (1) COVID-19, (2) mobility, (3) geographical variables, and (4) socioeconomic variables. The main results show that mobility has a negative relationship with the probability of an increase in COVID-19 cases and deaths until the ninth week of the pandemic, but a positive relationship from the eleventh week. We also find that socioeconomic variables such as GDP per capita and life expectancy have positive associations with the probability of an increase in

1 We are grateful to the valuable contributions of Kathiusca Montenegro. We are also grateful for valuable and enlightening comments by Guillermo Rochabrún, Oswaldo Molina, Arlette Beltrán, and the anonymous reviewers of this article. Corresponding author: Luis Palomino (luis.palomino 1390@gmail.com)

COVID-19 cases and deaths, while geographical variables such as terrain altitude and gradient have negative associations. The results also indicate show that the role of geographical and socioeconomic variables depend on the inclusion of Lima in the empirical analysis.

Keywords: COVID-19, mobility, panel data, Peru.

JEL classification: I1, C23, O54.

1. Introduction

The pandemic caused by coronavirus disease 2019 (COVID-19) reached Latin American shores on February 26, 2020, when Brazil announced the first case in São Paulo. One month later, countries in the region had shut their schools and airports, closed down businesses, and implemented a raft of restrictions in an attempt to control the spread of the virus. However, statistics indicate that the measures taken were of limited effectiveness sin-ceby the end of January 2021, more than 600,000 deaths from COVID-19 were recorded throughout the region.[2]

Peru was one of the first countries in Latin America to lock down its citizens with a view to containing transmission. On March 16, 2020 the government declared a state of health emergency, closed its borders, ordered the population to remain indoors except for the purchase of essential goods such as groceries or medication, and implemented curfews of varying lengths in all its cities. Initially, the lockdown was imposed for a period of two weeks, but the situation continued to deteriorate and it was prolonged until June 30, 2020. Still, despite these measures, Peru is considered one of the Latin American countries most affected by the pandemic. For this reason, several studies have sought to analyze the effects of the measures implemented by the Peruvian government, along with socioeconomic and geographical variables, on the severity and spread of the virus (Atalan, 2020; Fernandes et al., 2020; Nguimkeu & Tadadjeu, 2020).

On the one hand, empirical research suggests that the government measures to promote social distancing—through lockdowns, for instance—significantly reduced the propagation of the coronavirus (Atalan, 2020). However, it is worth noting that the social distancing measures also had adverse effects on human behavior and psychology, the environment, and the economy (Atalan, 2020; Wang & Li, 2021).

On the other hand, the results of worldwide empirical studies show that certain socioeconomic variables are positively associated with the number of COVID-19 cases. For instance, Nguimkeu and Tadadjeu (2020), using data from 182 countries, found that population density, the proportion of the population aged 65 and over, and urbanization are positively associated with the number of people infected with COVID-19. The authors also found that income level and quality of health infrastructure do not have significant effects on the spread of the virus.

2 https://www.as-coa.org/articles/el-coronavirus-en-america-latina

Results of empirical studies also indicate that geographical variables have major effects on the evolution of COVID-19 cases and deaths. It has been noted that mean temperature has a negative effect on the number of coronavirus cases (Nguimkeu & Tadadjeu, 2020). However, the geographical variable that has sparked the liveliest theoretical and empirical debate is altitude. Some studies suggest that altitude is negatively related to the number of cases and deaths from the virus (Arias-Reyes et al., 2020; Fernandes *et al.*, 2020). These studies point out that high altitude is characterized by drastic changes of temperature from day to night, dry air, and elevated levels of ultraviolet radiation (Arias-Reyes et al., 2020). In particular, UV-A and UV-B radiation can alter the molecular strands between DNA and RNA, so at high altitudes radiation can act as a natural disinfectant (Andrade, 2020; Zubieta-Calleja, 2020; Zubieta-Calleja & Zubieta-DeUrioste, 2017). Other studies argue that it is still too early to draw conclusions about the impacts of high altitudes on the severity and progression of the pandemic without an assessment of other social, demographic, and risk factors along with health variables (Huamaní et al., 2020).

Understanding the different factors that are conditioning the evolution of COVID-19 deaths could be key to designing preventative policies aimed at minimizing large-scale economic and social losses during this and future pandemics. Indeed, in a study on epidemics in Peru, García Cáceres (2002) proposes that the quarantine declared in 1833 following the outbreak of Asiatic cholera proved effective due to Peru's geographical qualities, in that the sulfurous sand of the coastal desert acted as a natural barrier that thwarted the transmission of the disease from one oasis to the next, between Tumbes in the north and Tarapacá in the south. This meant that a cholera sufferer in Paita could not readily transmit the disease to nearby towns because the desert impeded rapid spread from one population or valley to another. Thus, the policies implemented in response to each epidemic should take into account the buffers provided by Peruvian geography.

In this vein, the present study seeks to contribute to the literature on the determinants of COVID-19 cases and deaths in Peru by focusing on the role of human mobility (measured as the proportion of people who travel more than one kilometer per day), geography, and economic development. To this end, we employ Poisson regression with random effects and data from four groups of variables at the district level:
(1) COVID-19, (2) mobility, (3) geographical variables, and (4)socioeconomic variables.

Among the key results, we find that mobility has a negative relationship with the likelihood of an increase in COVID-19 cases and deaths up to the ninth week of the pandemic, but a positive effect from the eleventh week. We also find that socioeconomic variables such as GDP per capita and life expectancy have positive associations with the probability of COVID-19 cases and deaths increasing, while geographical variables, such as the altitude and gradient of the terrain, have negative associations. The results also reveal that the role of geographical and socioeconomic variables varies according to whether or not Lima—which accounts for around one third of Peru's population—is included in the empirical analysis.

The rest of this article is structured as follows: in the second section, we describe the data and the methodology employed; in the third and fourth sections, we present our results; and finally, in the fifth and sixth sections, we discuss the conclusions and limitations of this study and provide suggestions for future lines of research.

2. Data and methodology

2.1 Data

In this study, we use four groups of variables: (1) COVID-19, (2) mobility, (3) geographical, and (4) socioeconomic.

<u>COVID-19</u>

This group encompasses the number of COVID-19 cases and deaths. The data on cases and deaths is taken from the Peruvian Ministry of Health (MINSA).[3] Data on deaths is also provided by the National Information System on Fatalities (SINADEF).[4] However, even with the most-up-to-date information, we find differences when we compare the number of deaths recorded by MINSA with those of SINADEF (see Annex 1). Moreover, the updated MINSA data shows the presence of deaths from COVID-19 that predate the first recorded cases. The MINSA team tasked with updating the data provided the following explanation:

> When an epidemic occurs it is not uncommon that the first cases diagnosed by the health services, and which are made public, are not really the first to occur—all the more so when this is a new disease whose clinical manifestations can be confused with other conditions and escalate rapidly to the point of death. Epidemiological surveillance and retrospective analysis

3 For MINSA data, see: https://www.datosabiertos.gob.pe/group/datos-abiertos- de-covid-19

4 For SINADEF data, see: https://www.datosabiertos.gob.pe/dataset/información-de-fallecidos-del-sistema-informático-nacional-de-defunciones-sinadef-ministerio

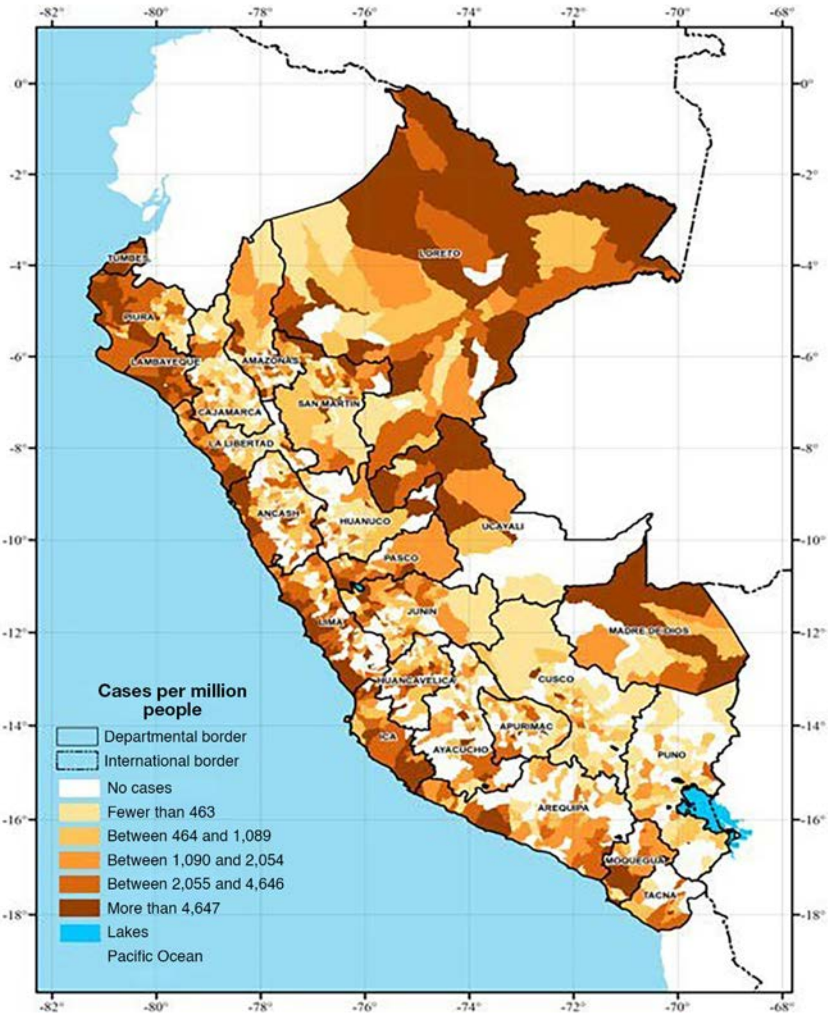
> of cases and fatalities enable identification of some cases (generally very few) that may have presented themselves earlier and which allow for a clearer idea of the disease's transmission. As was mentioned in the beginning, it is not unusual for this to occur in every country and not only in the case of COVID-19.[5]

MINSA statistics on Peruvian COVID-19 cases start on March 6, 2020, the day on which the first patient tested positive, while the most up-to-date statistics on the number of deaths show that the first COVID-19 fatality occulted on March 3.

Figures 1 and 2 present groups of districts according to the overall number of COVID-19 cases and deaths per million people. The darkest colors correspond to the districts with the highest numbers of cases and deaths per million inhabitants, while white denotes those districts for which no information is available. These statistics reveal that the coastal districts had the highest numbers of cases and deaths per million people. The figures also show large numbers of COVID-19 cases recorded in districts in Amazonia (Fluvial Yunga, central, and low selva). The Amazonian districts with high death rates per million people correspond to departmental capitals or their environs, such as Loreto in the department of Loreto, Puerto Maldonado in Madre de Dios, and Pucallpa in Ucayali. Conversely, Andean districts (containing the natural regions of Quechua, Suni, Puna, and Janca) are those with the lowest numbers of deaths and cases per million residents. Similarly, Andean Peru has the highest number of districts without any recorded deaths from the virus.

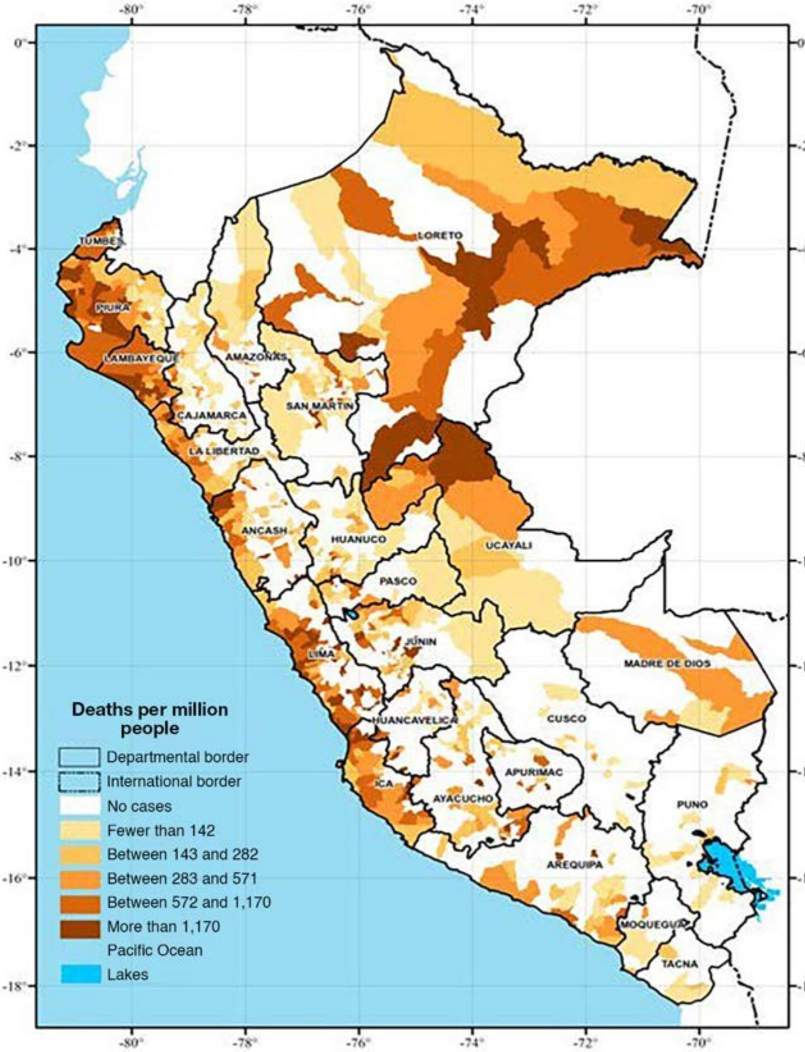
5 For more detail, see: https://cdn.www.gob.pe/uploads/document/file/1920118/Informe%20final%20del%20grupo%20de%20trabajo%20te%CC%81cnico%20con%20cifra%20de%20fallecidos%20por%20la%20COVID-19.pdf.pdf. All translations from Spanish are by Apuntes.

Figure 1
COVID-19 cases – district level



Source: MINSA. Compiled by authors.

Figure 2
COVID-19 deaths – district level



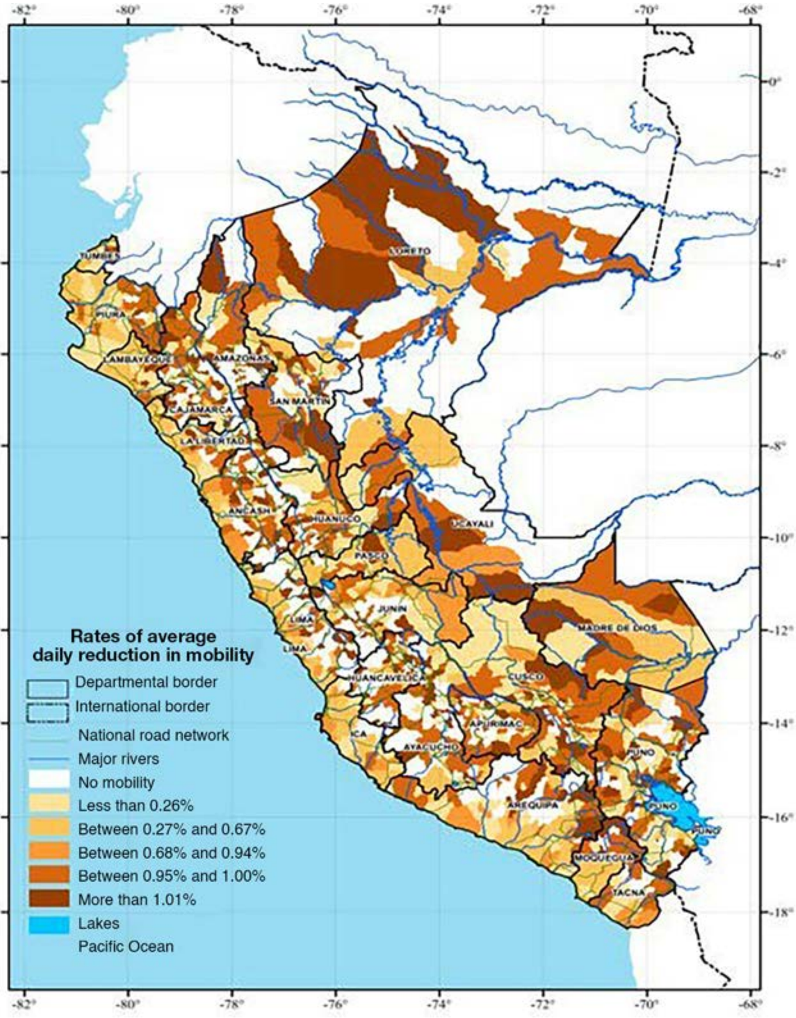
Source: MINSA. Compiled by authors.

Transportation

This group includes a measure of human mobility. The data are from the Inter-American Development Bank (IDB) and cover the period March 06 to June14, 2020.[6] As noted, the indicator we use for mobility corresponds to the proportion of the population who travel more than one kilometer in a single day, and has been constructed using georeferenced data from cell phones. For more detail on the mobility data collected by the IDB for 22 Latin American countries, see Aromí et al. (2020, 2021).

6 For regional data on mobility, consult: https://www.iadb.org/es/investigacion-y-datos/movilidad-covid

Figure 3
Mobility – district level



Source: IDB. Compiled by authors.

Figure 3 shows the average daily rate of mobility reduction. In this figure, the darkest color represents the districts in which mobility decreased the most, while the lightest color denotes those districts with the lowest reduction rates. The figure also shows the national road network, in green, in order to determine whether there is a spatial relationship between mobility and proximity to roads. The statistics in this figure show that the coastal districts and those that correspond to capitals or the biggest cities in a department are those in which mobility declined the least. It can also be seen that certain Andean districts, in which several branches of the national road networks come together, belong to the group with the highest daily reductions in mobility. These results seem to indicate that the social distancing policies implemented by the government may have served to decrease mobility around highway intersections precisely because people were unable to travel. But to verify this hypothesis we conducted an empirical analysis using regressions.

Geographical

This group incorporates variables measuring the distance from settlements to the national road network, Camino del Inca,[7] the nearest port, and the coast. These geographical variables are also used by Seminario et al. (2019) to analyze the historical evolution of Peru's regional inequality, drawing on department-level data for the 1795–2018 period. The geographical variables also include average terrain gradient and width of the Andean Mountains. These variables are used by Seminario and Palomino (2021) to analyze how population and the concentration of economic activity evolved in Peru, at the province level, between 1795 and 2018. However, in this study we obtained our district-level data on settlements from the 2017 population census and the ARcGIS software package. One of Peru's most important geographical factors is the Andean mountains, with their high altitudes(Seminario & Palomino, 2021). Thus, in the present study we also take into account another two geographical variables: width of the Andean Mountains, and average terrain gradient. Seminario and Palomino (2021) determine the width of the Andean Mountains using the 2.300 m.a.s.l contour line, defined as the horizontal distance between the limits of the Sea Yunga and the Fluvial Yunga in South America. This indicator is important because the width of this geological feature can affect population movement and can be used to determine the extent of highland terrain.

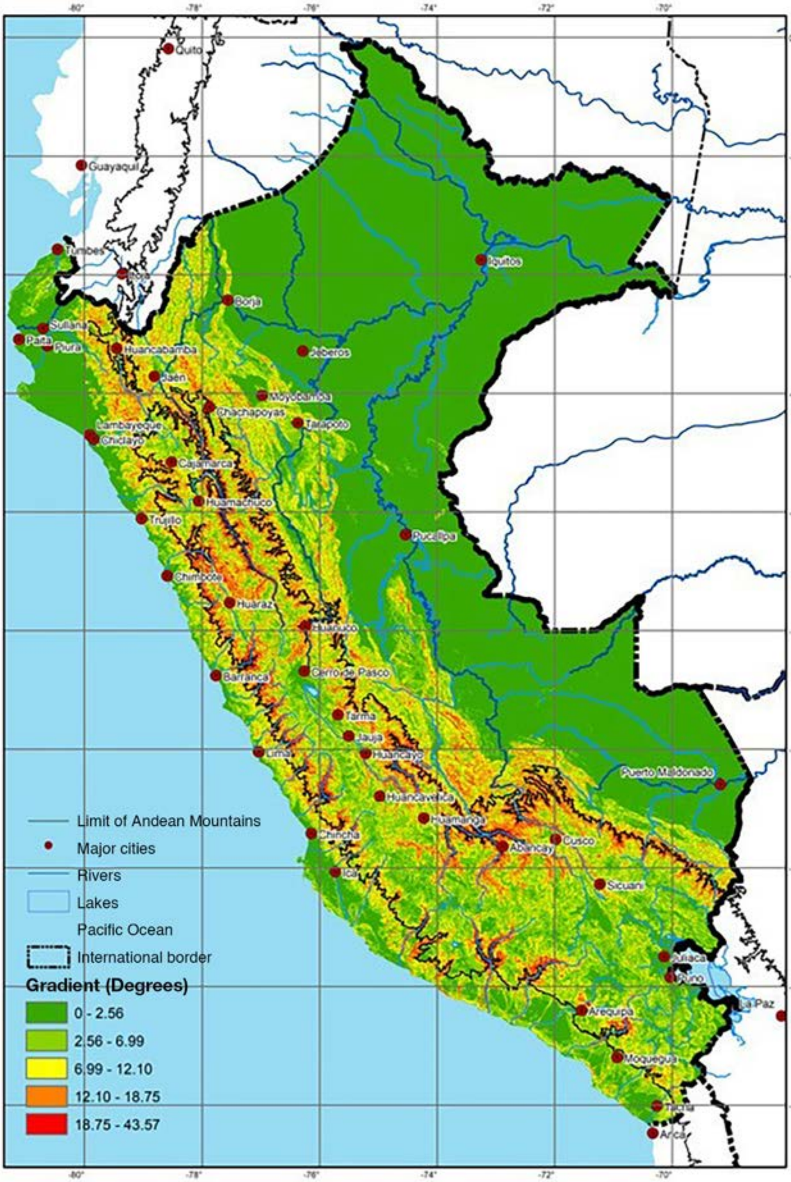
We also include average terrain gradient because the previous indicator does not provide information on territorial relief. Terrain gradient can serve to identify different kinds of relief, such as mountains, plateaus, and valleys. This variable was also created by Seminario and Palomino (2021), using the

7 The Camino del Inca, or Qhapaq Ñan, is the pre-Colombian road network that not only played an important role during the Inca empire but was also a key component of the economy when most of South America was under Spanish dominion. (Franco, Galiani, & Lavado, 2021). Likewise, Seminario and Palomino (2021), using georeferenced maps, find that Peru's major colonial and modern cities were founded in the areas connected by the Camino del Inca. This implies that the network's proximity to urban centers may play a key role in the spread of pandemics.

30-meter contour lines in South America. We also employ average terrain altitude, which is generated based on the digital elevation model available on ArcGIS, created by the Earth Resources Observation and Science Center in Sioux Falls, South Dakota.

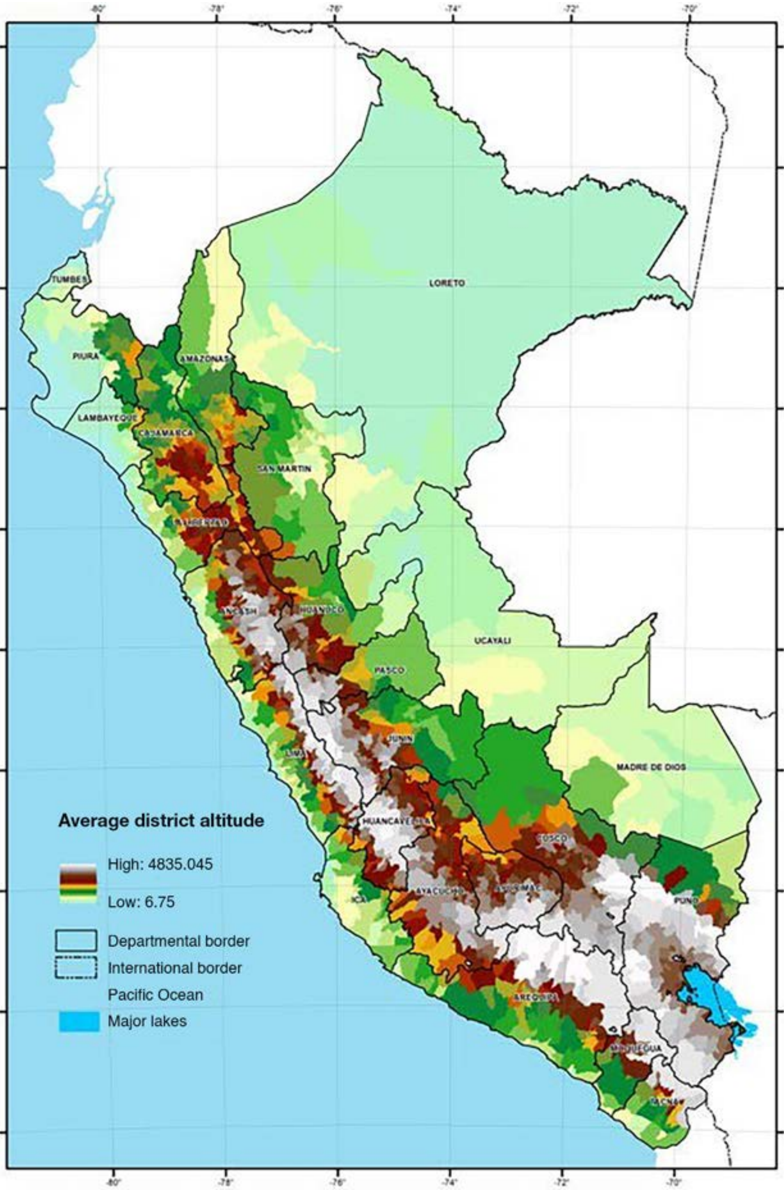
In Figures 4 and 5 we display the districts of Peru according to average gradient and altitude. On the one hand, Figure 4 shows that Peru's coastal region has a low gradient, which facilitates movement from one area to another, while the steeper highlands creates a natural barrier to mobility. It should also be noted that the Andes also include flat areas, but these correspond to the Suni, Puna, and Janca areas located above 3,500 m.a.s.l. Thus, it can be surmised that the lower total of COVID-19 cases and deaths in Andean districts may be a consequence of natural barriers hampering transmission. On the other hand, Figure 5 shows that the northern and central coast has districts with a lower average altitude than those located along the northern littoral. Finally, the figure reveals that Amazonian districts have a similar altitude to those on the northern and central coast. These results suggest that altitude is negatively related to the number of deaths and cases of coronavirus. In any case, we use regressions to verify the empirical relationship that average gradient and altitude have with the evolution of COVID-19 cases and deaths.

Figure 4
Average gradient



Source: Seminario & Palomino (2021). Compiled by authors.

Figure 5
Average altitude



Source: Seminario & Palomino (2021). Compiled by authors.

Socioeconomic

This group takes into account variables related to poverty, education, income per capita, and settlement size. To this end we drew on three sources: Peru's National Institute of Statistics and Informatics (Instituto Nacional de Estadística e Informática, INEI), Seminario and Palomino (2022), and the UN Development Program (UNDP).

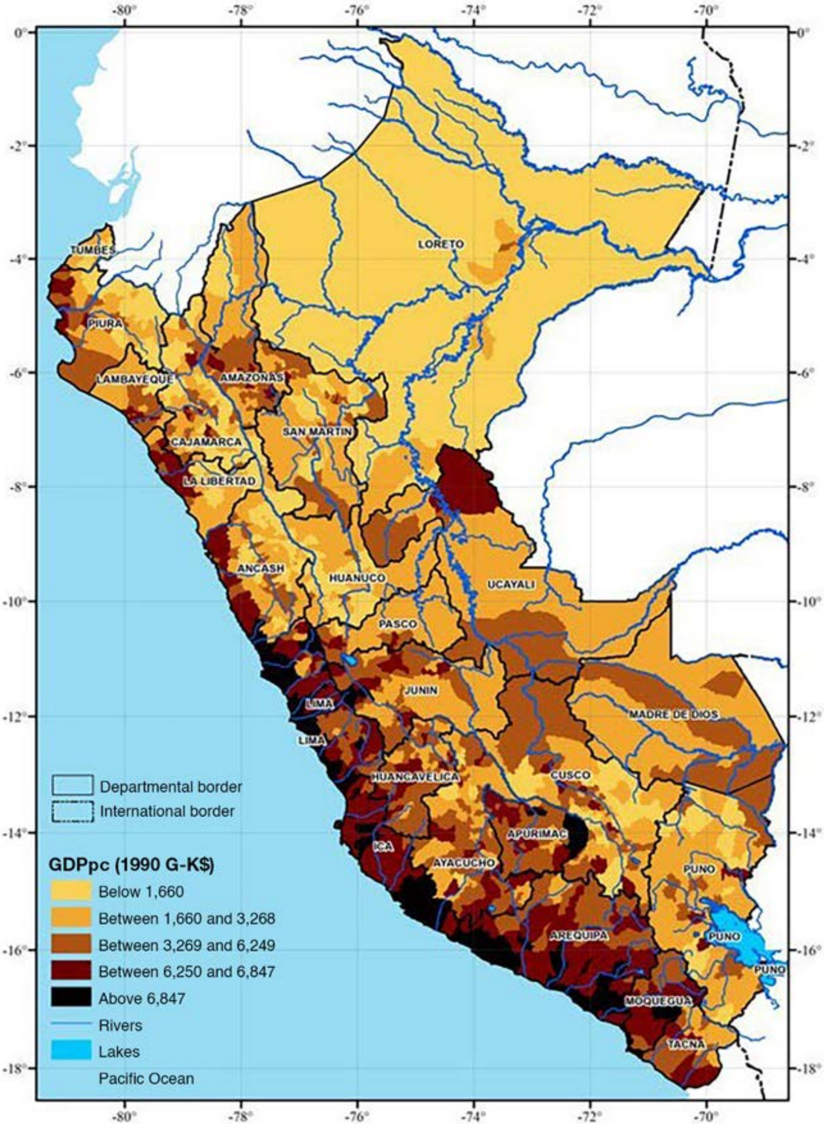
We obtained series on poverty at the district level from INEI (2020) This variable is relevant in that numerous studies have found that the poor are more vulnerable to the coronavirus. Michael Ryan, the executive director of the World Health Organization Health Emergencies Programme, points out that lifestyles attributable to poverty as well as limited access to health services leave people susceptible to COVID-19 and associated complications (WHO, 2020).

Along these same lines, the inclusion of per capita is relevant to our analysis. Seminario and Plomino (2022) calculated GDP per km^2 at the level of Peruvian provinces and districts for the period 1993-2018. The authors also created annual series on settlement population density and average settlement size, running from 1993 to 2018.

Figures 6 and 7 show the spatial distribution of GDP per capita and GDP per km^2, respectively, at the district level for 2018. According to these figures, the districts with the highest levels of GDP per capita and GDP per km^2 are located along the coast, in the departmental capitals of Amazonia, in Andean mining areas, and in regions engaged in export agriculture. These results suggest that the districts with the highest rates of COVID-19 cases and deaths are also those with the highest levels of GDP per capita and GDP per km^2.

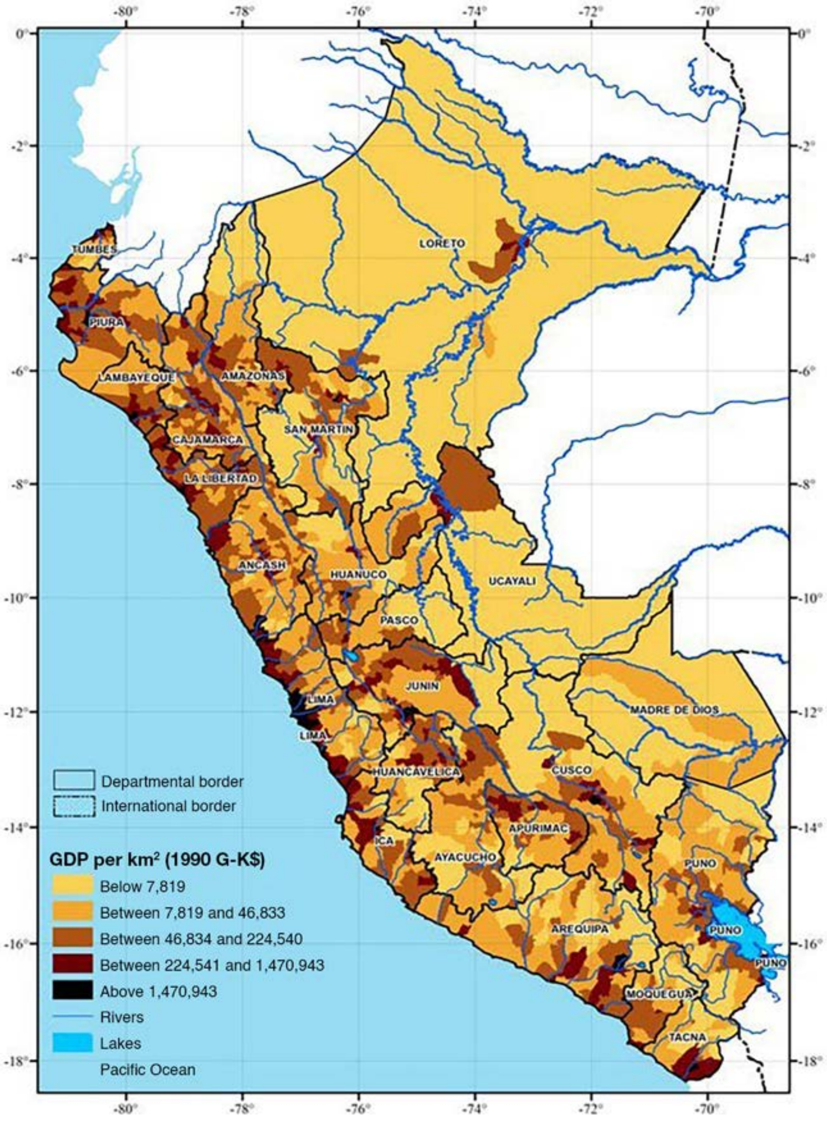
Finally, our empirical analysis also takes into account the Human Development Index (IDH) and its components (life expectancy, education, and income per capita) for 2019, which were calculated by PNUD (2019).

Figure 6
GDP per capita, 2018



Source: Seminario & Palomino (2022). Compiled by authors.

Figure 7
GDP per km², 2018



Source: Seminario & Palomino (2022). Compiled by authors.

2.2 Methodology

To evaluate the relationship between mobility and the evolution of COVID-19 cases and deaths at the district level in Peri, we used the panel data methodology. This allowed us to incorporate both the temporal and the transversal dimensions the series captured. However, we used random-effects panel regressions because the geographical and socioeconomic variables that we factor into the empirical analysis have no temporal dimensions. In addition, we employ Poisson models due to the presence of many zeros in the COVID-19 database (Henderson, Storeygard, & Weil, 2020). As a result, the general empirical model to be estimated is as follows:

$$\Pr(Y_{i,t}) \mid \mathrm{X}) = \exp(X'\beta)$$

$$\Pr(Y_{i,t} \mid \mathrm{X}) = \exp(\beta_0 + \beta_1 \ln(Mobility)_{i,t} + \beta_2 \ln(GV)_i + \beta_3 \ln(SEV)_i + e_i)$$

Where Y corresponds to total COVID-19 cases or deaths per million people, and ***Mobility*** relates to the percentage of the population that traveled more than one kilometer per day. The geographical variables (GV) comprise the distance between settlements and the nearest port, the distance of to the Camino del Inca, the distance to the coast, and the distance to the national road network, as well as the width of the Andean Mountains and average terrain gradient and altitude. In turn, the socioeconomic variables (SEV) include poverty, GDP per capita, GDP per km^2, the HDI and its components, average settlement size, and population density. Finally, $e_{t,i}$ corresponds to the estimation error. Given that the regressors are expressed in natural logarithms, the parameters estimated correspond to the elasticities.

The period of empirical analysis is restricted by the availability of data on population mobility, which runs from March 6 to June 14, 2020. Meanwhile, the regressions take into account a sample of 1,834 districts, of which 1,197 have information available on mobility.

3. Results

In Table 1, we show the correlations between the four groups of variables included in this regression: (1) COVID-19, (2) mobility, (3) geographical, and (4) socioeconomic.

Table 1
Pearson correlation at district level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Cases	1,00									
2. Deaths	**0,77*** **	1.00								
3. Mobility	0.40***	0.36***	1.00							
4. Distance to nearest port	-0,18***	-0.19***	-0.20***	1.00						
5. Distance to Camino del Inca	-0.02***	0.04***	-0.07***	-0.05***	1.00					
6. Distance to national road network	-0.05***	-0.03***	-0.07***	-0.01	**0.64*** **	1.00				
7. Distance to coast	-0.12***	-0.08***	-0.17***	**0.52*** **	**0.72*** **	0.44***	1.00			
8. Gradient	-0.14***	-0.16***	-0.16***	**0.52*** **	-0.23***	-0.07***	0.09***	1.00		
9. Width of Andean Mountains	-0.15***	-0.16***	-0.14***	**0.53*** **	-0.21***	-0.00	0.25***	0.39***	1.00	
10. Altitude	-0.18***	-0.19***	-0.18***	**0.59*** **	-0.27***	-0.05***	0.24***	**0.53*** **	**0.73*** **	1.00
11. GDP per capita	0.31***	0.25***	0.47***	-0.37***	-0.23***	-0.17***	-0.44***	-0.20***	-0.16***	-0.27***
12. GDP per km^2	0.39***	0.32***	**0.50*** **	-0.25***	-0.10***	-0.07***	-0.22***	-0.24***	-0.17***	-0.23***
13. Population density	0.39***	0.34***	0.47***	-0.25***	-0.11***	-0.09***	-0.23***	-0.26***	-0.18***	-0.24***
14. HDI	0.24***	0.21***	0.35***	-0.48***	-0.17***	-0.18***	-0.47***	-0.35***	-0.24***	-0.40***
15. Settlement size	**0.58*** **	**0.56*** **	**0.67*** **	-0.22***	-0.08***	-0.07***	-0.19***	-0.13***	-0.16***	-0.19***
16. Poverty	-0.15***	-0.13***	-0.23***	0.38***	0.07***	0.17***	0.33***	0.34***	0.22***	0.41***
17. Life expectancy	0.12***	0.11***	0.14***	-0.32***	-0.12***	-0.11***	-0.35***	-0.17***	-0.25***	-0.33***
18. Level of education	0.21***	0.19***	0.33***	-0.34***	-0.21***	-0.23***	-0.38***	-0.34***	-0.05***	-0.20***
19. Income per capita	0.24***	0.21***	0.35***	-0.48***	-0.12***	-0.13***	-0.43***	-0.31***	-0.26***	-0.40***

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
11. GDP per capita	1.00								
12. GDP per km_2	**0.62*** **	1.00							
13. Population density	**0.56*** **	**0.95*** **	1.00						
14. HDI	**0.75*** **	0.44***	0.44***	1.00					
15. Settlement size	0.46***	**0.53*** **	**0.55*** **	0.31***	1.00				
16. Poverty	**-0.56*** **	-0.28***	-0.29***	**-0.80*** **	-0.16***	1.00			
17. Life expectancy	0.35***	0.20***	0.21***	0.48***	0.16***	-0.34***	1.00		
18. Level of education	**0.69*** **	0.40***	0.41***	**0.88*** **	0.26***	**-0.77*** **	0.25***	1.00	
19. Income per capita	**0.74*** **	0.47***	0.44***	**0.95*** **	0.33***	**-0.72*** **	0.36***	**0.75*** **	1.00

Notes. This table presents the correlations between all variables included in the empirical analysis. The statistics take into account a sample of 1,834 districts. Statistical significance at the 0.1%, 1%, and 5%, levels are denoted with ***, **, and *, respectively.

First, the statistics indicate a 77% correlation between the number of deaths and the number of cases of COVID-19, while the correlation between mobility and the number of cases and the number of deaths is 40% and 36%, respectively. This suggests that greater population mobility could result in a spike in the number of cases and deaths caused by the pandemic.

Second, the statistics show that there is a negative relationship between the geographical variables and the number of cases. However, not all geographical variables have a negative relationship with the number of deaths. The results suggest a positive relationship between the number of deaths and the average distance between settlements and the Camino del Inca. This may be because fatalities from COVID-19 among those located far from the Camino del Inca could be more likely due to difficulties in receiving timely treatment at a medical center. However, future research should incorporate geolocation variables on deaths from the virus to confirm this hypothesis.

The results in columns 4–10 suggest a correlation of greater than 50% between certain geographical variables. For example, we detect a positive correlation of 64% between average distance to the Camino del Inca and to the national road network. We also find that average altitude has a positive correlation of 59% with average settlement distance to the nearest port, of 53% with average gradient, and 73% between the width of the Andes. The results also reveal that average distance between settlements and the nearest port has a positive correlation of 52% with average distance to the coast and average gradient, and of 53% with the width of the Andes. To avoid problems of multicollinearity in the regressions, we use those variables that have a correlation of less than 50%.

Third, the statistics show that the socioeconomic variables, except for those measuring poverty, have a positive correlation with the number of COVID-19 cases and deaths. Observing the rest of the correlations, we find some possible problems of multicollinearity among the socioeconomic variables. For example, we find that GDP per capita has a 62% correlation with GDP per km^2, 56% with population density, -56% with poverty, 75% with the HRI, 69% with life expectancy, and 74% with income per capita. Therefore, as with the group of geographical variables, to avoid problems of multicollinearity we select those that have a correlation of below 50%.

Although we have identified interesting relationships between the variables, we use regressions in order to deepen the empirical analysis. We confirm that there are no multicollinearity problems in the regressions analysis because the variance inflation factor (VIF) is below 10. In Tables 2 and 3 we show the results of Poisson regression with random effects at the district level. Moreover, with a view to analyzing the importance of Lima, the tables display the results with and without the capital.[8] These results show that mobility has significant positive relationships, with a 99% confidence interval, with the number of cases and deaths caused by the pandemic. The findings also reveal there are no significant positive differences in the magnitude of the association for mobility when Lima is excluded from the regressions.

According to the results presented in Table 2, the 1% increase in mobility is associated with an increase of around 0.16% in the probability of an increase in cases per million inhabitants when Lima is included, and of around 0.18% when it is excluded. The results also show that this magnitude achieves a value of 0.1671% when we incorporate the geographical and socioeconomic variables in the regressions that include Lima, while for the regressions that exclude Lima, the level of association for mobility attains a value of 0.1864%.

The results in Table 2 also reveal that the geographical variables have a negative relationship with the number of cases per million people. According to the regressions that include and exclude Lima, only high average altitude has a significant association, with a 95% confidence interval.

The regressions incorporating all the variables show that a 1% increase in average altitude is negatively associated with the probability of a rise in cases per million people, by 0.4439% when Lima is included and 0.3804% when it is excluded. This implies that altitude acts as a natural barrier, preventing an increase in transmission. These results are in line with those found by prior studies of the Peruvian case (Accinelli & León-Abarca, 2020; Intimayta-Escalante, Rojas-Bolívar, & Hancco, 2020; Seclén et al., 2020; Segovia-Juárez, Castagnetto, & Gonzales, 2020). On the one hand, using panel regressions and department-level data, Seclén et al. (2020) find a negative relation between average altitude and the total number of cases. On the other hand, using linear regressions, Segovia-Juárez et al. (2020) also find a negative relationship between the altitude of the provincial capitals and the number of cases of COVID-19.

The results in Table 2 also indicate that the socioeconomic variables have a negative relationship with the number of cases per million people. However, the level of statistical significance and the magnitude of associations depend on the inclusion of Lima in the regressions. The results show that GDP per capita has a positive and significant effect on the probability of an increase in cases of coronavirus per million people when Lima is included in the regressions; but when Lima is excluded, the association is only significant when geographical associations are controlled for. The 1%

8 Lima, as defined here, includes all districts in the department of Lima, as well as all districts in the constitutional province of Callao.

increase in GDP per capita is related to an increase of around 0.8521% in the probability of more cases per million inhabitants when Lima is included, and of around 0.5144% when the city is excluded.

On the other hand, the results indicate that settlement size is positively related to the probability of an increase in cases per million people. However, the positive relationship is only significant when Lima is excluded, or when Lime is included but geographical variables are not controlled for. This suggests that urban regions are those that face a greater likelihood of an increase in cases per million people, given that settlement size is greater than in rural areas. According to these results, the 1% increase in settlement size is positively associated with the probability of a 0.1190% increase in the number of cases per million people in the districts not located in Lima.

Table 3 shows the results of the relationship that mobility, geographical variables, and socioeconomic variables, respectively, have with the total number of deaths per million people at the district level.

Table 2
District-level results: cases of COVID-19

A: Including Lima

	(1)	(2)	(3)	(4)
Ln (Mobility)	0.1689***	0.1671***	0.1679***	0.1671***
	(0.0188)	(0.0189)	(0.0188)	(0.0189)
Ln (Distance to Camino del Inca)		-0.1255**		-0.0019
		(0.0491)		(0.0471)
Ln (Gradient)		0.0619		-0.0087
		(0.1137)		(0.0797)
Ln (Altitude)		-0.5829***		-0.4439***
		(0.0580)		(0.0686)
Ln (GDP per capita)			0.6028***	0.8521***
			(0.2140)	(0.2076)
Ln (Settlement size)			0.2127***	0.0111
			(0.0645)	(0.0559)
Ln (Life expectancy)			0.8117*	-0.0004
			(0.4513)	(0.4494)

B: Not including Lima

	(1)	(2)	(3)	(4)
Ln (Mobility)	0.1979***	0.1962***	0.1962***	0.1962***
	(0.0248)	(0.0248)	(0.0248)	(0.0248)
Ln (Distance to Camino del Inca)		-0.1541***		-0.0576
		(0.0364)		(0.0472)
Ln (Gradient)		-0.1496*		-0.0906
		(0.0768)		(0.0787)
Ln (Altitude)		-0.4750***		-0.3868***
		(0.0638)		(0.0704)
Ln (GDP per capita)			0.2467	0.5151***
			(0.1578)	(0.1615)
Ln (Settlement size)			0.3786***	0.1260***
			(0.0469)	(0.0453)
Ln (Life expectancy)			1.2012***	0.4670
			(0.4020)	(0.4007)

Notes. This table presents the elasticities estimated between the probability of an increase in the number of COVID-19 deaths per million people, the geographical variables, and the socioeconomic variables. Elasticities have been estimated using Poisson models with random effects. The regressions take into account a sample of 1,834 districts.

The regressions in columns (1), (2), and (3) take as independent variables mobility, the geographical variables, and the socioeconomic variables, respectively. Column (4) presents the estimated elasticities taking into account all variables included in columns (1) to (3). The regressions in Panel A include all districts, while those in Panel B exclude the districts of the department of Lima and the constitutional province of Callao. Robust standard errors are presented in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted with ***, **, and *, respectively.

Table 3
District-level results: deaths from COVID-19

A: Including Lima

	(1)	(2)	(3)	(4)
Ln (Mobility)	0.1757***	0.1730***	0.1757***	0.1730***
	(0.0230)	(0.0231)	(0.0230)	(0.0231)
Ln (Distance to Camino del Inca)		-0.0380		0.0631
		(0.0623)		(0.0570)
Ln (Gradient)		-0.0222		-0.2659***
		(0.1460)		(0.0976)
Ln (Altitude)		-0.6293***		-0.4326***
		(0.0829)		(0.0955)
Ln (GDP per capita)			0.4396	0.9576***
			(0.2873)	(0.2713)
Ln (Settlement size)			0.2780***	-0.0708
			(0.0758)	(0.0664)
Ln (Life expectancy)			1.6656***	1.2736**
			(0.6431)	(0.6088)

B: Not including Lima

	(1)	(2)	(3)	(4)
Ln (Mobility)	0.1968***	0.1968***	0.1968***	0.1968***
	(0.0344)	(0.0344)	(0.0344)	(0.0344)
Ln (Distance to Camino del Inca)		-0.0849*		0.0021
		(0.0509)		(0.0564)
Ln (Gradient)		-0.2972***		-0.3800***
		(0.1017)		(0.0977)
Ln (Altitude)		-0.5094***		-0.3613***
		(0.0878)		(0.0927)
Ln (GDP per capita)			0.1133	0.5866***
			(0.2126)	(0.2163)
Ln (Settlement size)			0.4756***	0.0305
			(0.0720)	(0.0652)
Ln (Life expectancy)			1.9710***	1.5187***
			(0.5662)	(0.5685)

Notes. This table presents the elasticities estimated between the probability of an increase in the number of COVID-19 deaths per million people, the geographical variables, and the socioeconomic variables. Elasticities have been estimated using Poisson models with random effects. The regressions take into account a sample of 1,834 districts.

The regressions in columns (1), (2), and (3) take as independent variables mobility, the geographical variables, and the socioeconomic variables, respectively. Column (4) presents the estimated elasticities, taking into account all variables included in columns (1) to (3. The regressions in Panel A include all districts, while those in Panel B exclude the districts of the department of Lima and the constitutional province of Callao. Robust standard errors are presented in parentheses. Statistical significance at the 0.1%, 1%, and 5% levels are denoted with ***, **, and *, respectively.

First, the results in Table 3 show that mobility has a positive relationship with the probability of an increase in deaths per million people, regardless of whether or not Lima is taken into account. The regressions incorporating all the variables show that a 1% increase in mobility is positively associated with a 0.1730% increase in probability of a rise in cases per million people when Lima is included, and with a 0.3804% increase when the capital is not included. These results show that an increase in mobility, measured by the percentage of the population in the district that travels more than a kilometer, raises the likelihood of a rise in COVID-19 cases and deaths.

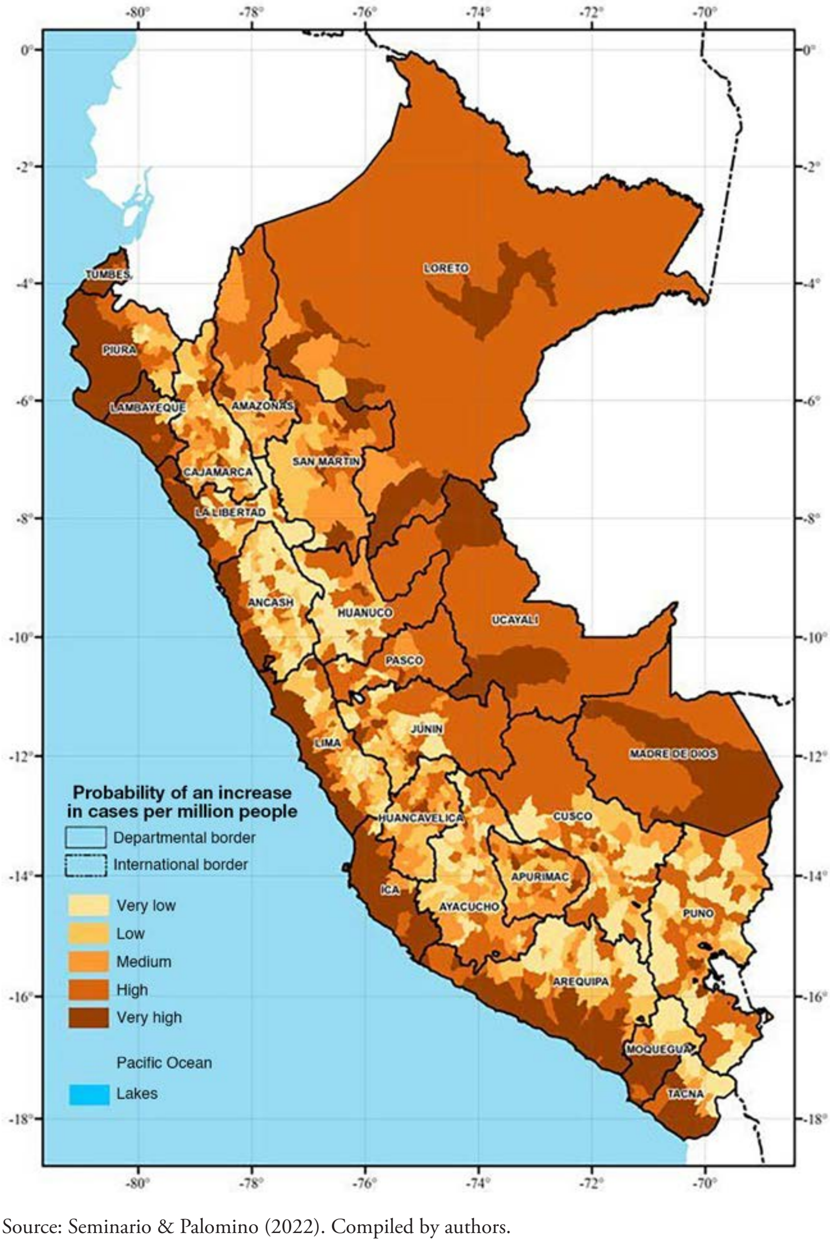
Second, the regressions show that average gradient and altitude have a negative relationship with the probability of an increase in deaths per million people. On the one hand, we find that a 1% increase in average gradient is negatively associated with a 0.2689% increase in the probability of a rise in cases per million people when Lima is included, and with a 0.3861% increase when Lima is excluded. On the other hand, a 1% increase in average gradient is negatively associated with a 0.4314% increase in the probability of a rise in cases per million people when Lima is included, and with a 0.3553% increase when Lima is excluded. In sum, the results indicate that the Peruvian regions containing areas with high altitudes and high case numbers are less likely to see an increase in deaths caused by a disease as contagious as COVID-19.

Third, the results show that some of the socioeconomic variables have a positive relationship with the probability of an increase in deaths per million people. Indeed, they show that the probability of an increase in deaths per million people is positively related with GDP per capita and life expectancy. These results suggest that, in Peru, the first wave of the pandemic caused more deaths in the departments with higher levels of economic development.

On the one hand, a 1% increase in GDP per capita is positively associated with a 0.9601% rise in the probability of more deaths per million people when Lima is included, and with a 0.5865% rise when Lima is excluded. That is, when Lima is excluded from the regressions, the magnitude of the empirical relationship of GDP per capita drops by 37 basic points. On the other hand, the results indicate that a 1% increase in life expectancy is positively associated at 1.2704% with the probability of more deaths per million people when Lima is included, and at 1.5277% when Lima is excluded. On the other hand, there is no clear empirical relationship between the probability of more deaths per million people and settlement size. Specifically, the results show that empirical relations go in the same direction with and without Lima, but the magnitude is greater when Lima is excluded in the majority of variables. Using the parameters estimated from the regressions that take into account all variables and exclude Lima, we compute the probability of an increase in deaths and cases per million people at the district level. Figures 8 and 9, show the spatial distribution of Peruvian districts by quintiles of probability of an increase in cases and deaths per million, respectively. In these figures, the darkest colors correspond to the greatest probability of an increase in cases and deaths per million people.

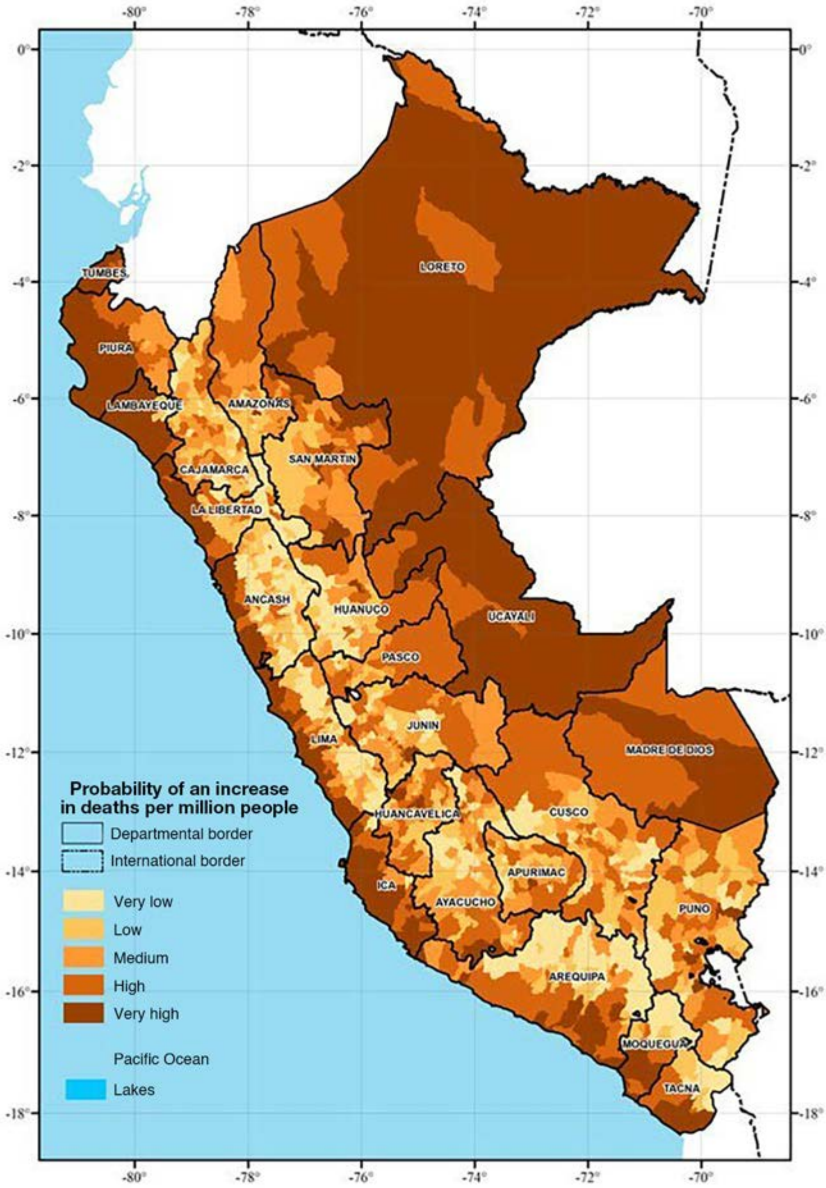
Figures 8 and 9 suggest that the districts located in the coastal and Amazonian regions are subject to greater probabilities of an increase in cases and deaths per million people. On the one hand, the coastal region is more likely to experience an increase in COVID-19 cases and deaths, because this region is home to 70% of the Peruvian population and has an average density of 111 people per km^2. On the other hand, it is apparent that Amazonia is another region with high probabilities of a rise in cases and deaths. These results may be attributable to the health conditions and habits of the population. While the major cities have access to highly trained healthcare professionals, most small health centers and rural communities have poor health infrastructure, equipment, and personnel (García, 2020). As the figures show, the highlands is the region with the fewest districts that have a high likelihood of a rise in COVID-19 cases and deaths, which may be due to natural barriers such as average gradient and altitude. However, we also observe districts with high probabilities of a rise in cases and deaths per million people: largely those that are departmental capitals, provincial capitals, and mining areas.

Figure 8
Probability of an increase in cases per million people



Source: Seminario & Palomino (2022). Compiled by authors.

Figure 9
Probability of an increase in deaths per million people



Source: Seminario & Palomino (2022). Compiled by authors.

4. Sensitivity analysis

In this section we discuss the evolution of empirical relationships according to the total number of weeks for which the pandemic has lasted. To this end, we use Model 4 in Tables 2 and 3. Figures 10 and 11 present the results for all Peruvian districts and for only those in Metropolitan Lima, respectively. In these figures, we only present the empirical relationships that are statistically significant at a 90% confidence level.

First, the results in Figures 10 and 11 indicate that the relationship between mobility and the probability of an increase in cases and deaths per million people was not positive for all weeks of the pandemic taken into consideration. In particular, a positive relationship can be observed from the 11th week of the pandemic, while in the previous weeks there was a negative relationship. On the one hand, the positive relationship can be explained by the resumption of certain economic activities that could not be continued during lockdown. These most likely occurred in the informal sector because our empirical analysis falls within the state-imposed lockdown that began on March 16 2020 and ended on June 30 2020.[9] This implies that prolonged lockdowns are unsustainable, because they can fuel a country's informal economy. On the other hand, the negative relationship may be capturing travel by pandemic-response personnel. This suggests that travel by medical professionals, the armed forces, and police officers may have contributed to controlling the spread of the virus during the first nine weeks of the pandemic. In sum, the results indicate that the role of mobility depends on the sector included in the empirical analysis.[10]

Second, the results of Figure 10 reveal that settlement size has a positive relationship with the probability of an increase in cases per million people in the first four weeks of the pandemic when all districts of Peru are taken into account, while Figure 11 shows a negative relationship between the fourth and eighth weeks when districts in Metropolitan Lima alone are factored in. Thus, with the exception of Metropolitan Lima districts, which display different dynamics, the biggest districts in Peru were the first to record cases of COVID-19. Third, Figures 10 and 11 indicate that GDP per capita has a positive relationship with the probability of an increase in deaths per million

9 For more details about Peru's nationwide lockdown, see: https://www.dw.com/es/per%C3%BA-levanta-cuarentena-con-285213-contagios-y-9677-muertos/a-54006409

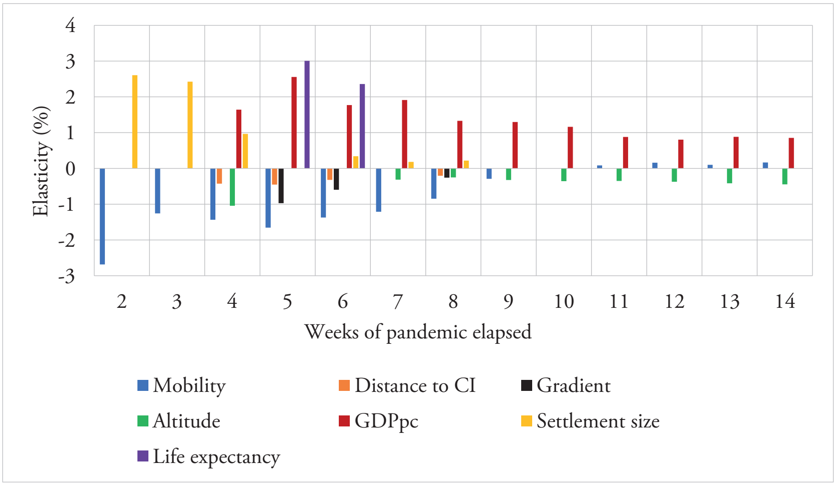
10 In order to identify the confidence interval of our results, we analyze the correlation between the mobility indicators we employ here with the mobility indicators devised by Google (2020). However, we conduct our analysis of correlations at the department (region) level because Google does not provide mobility indicators at the district level. In line with Aromí et al. (2021), we find a correlation of more than 90% between our mobility indicators and those generated by Google.

people. The positive association begins in the second week of the pandemic when Lima districts are included, and from the fourth week when districts throughout Peru are taken into account. Based on these results, we can say that the pandemic first spread in the Lima districts with the highest GDP per capita, and then reached other districts of Peru that likewise have high levels of GDP per capita.

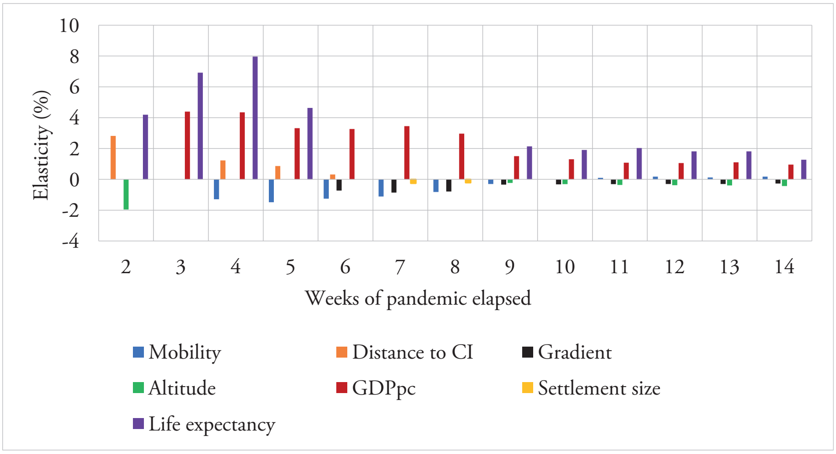
Fourth, the results shown in Figure 10 indicate that life expectancy has a positive relationship with the probability of an increase in deaths per million people in the first five weeks of the pandemic and after the eighth week, taking into account all districts of Peru. On the other hand, Figure 11 reveals that life expectancy is positively associated with the probability of an increase in cases per million people in Metropolitan Lima throughout the period of analysis, while the positive association with the probability of an increase in deaths per million people is observed from the eighth week. These results suggest that the districts with the highest life expectancy in Metropolitan Lima are the ones with the most cases, but because of the higher overall quality of healthcare there than in other regions of the country, these districts were able to reduce the probability of an increase in deaths in the first eight weeks of the pandemic. However, as of the ninth week, deaths increased in districts with the highest life expectancy throughout Peru.

Figure 10
Results per week of the pandemic, all Peru

A: Cases of COVID-19

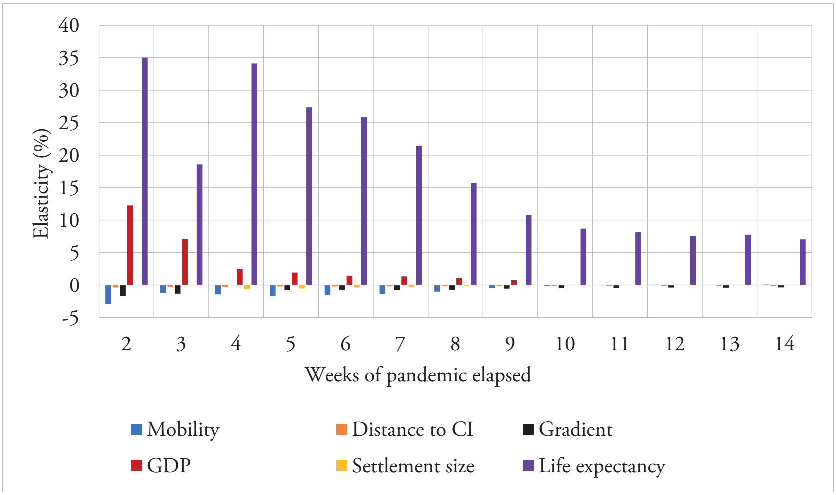


B: Deaths from COVID-19

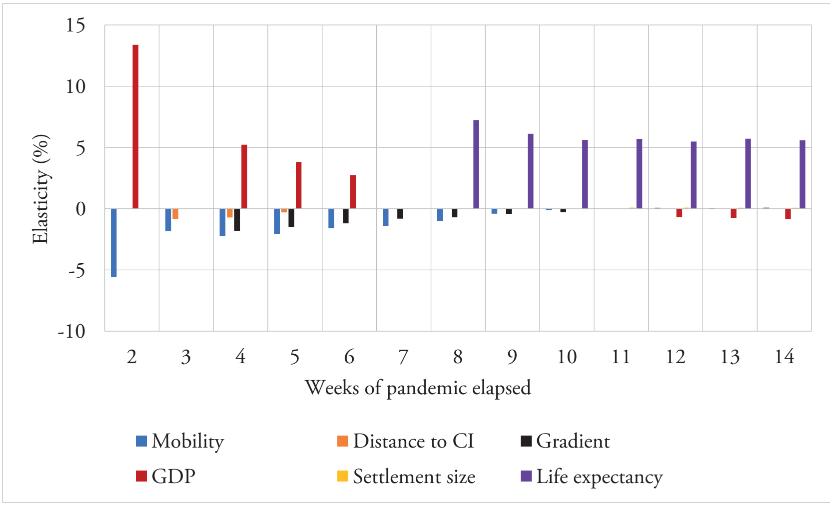


Notes. This figure presents the elasticities estimated between the probability of an increase in the number of COVID-19 cases and deaths per million people, the geographical variables, and the socioeconomic variables. Elasticities were estimated using Poisson models with random effects. The regressions take into account the empirical specifications, which include all variables that have no multicollinearity problems (Model 4 in Table 2 for cases, and Table 3 for deaths). The regressions take into account a sample of 1,834 districts throughout Peru. The graph presents only the significant elasticities with a 90% confidence interval.

Figure 11
Results per week of the pandemic, Metropolitan Lima A: Cases of COVID-19



B: Deaths from COVID-19



Notes. This figure presents the elasticities estimated between the probability of an increase in the number of COVID-19 cases and deaths per million people, the geographical variables, and the socioeconomic variables. Elasticities were estimated using Poisson models with random effects. The regressions take into account the empirical specifications, which include all variables that have no multicollinearity problems (Model 4 in Table 2 for cases, and Table 3 for deaths). The regions include a sample of 49 districts in Metropolitan Lima (provinces of Lima and Callao). The graph presents only the significant elasticities with a 90% confidence interval.

Finally, Figure 10 attests to a negative relationship between altitude and the probability of an increase in cases per million people from the seventh week of the pandemic, while a negative relationship between altitude and the probability of an increase in deaths per million people is observed from the ninth week. Likewise, we found a negative association between gradient and the probability of an increase in deaths per million people from the sixth week. On the other hand, Figure 11 indicates that gradient has a negative association with the probability of an increase in cases per million people when only the districts of Metropolitan Lima are taken into account, while a negative association between the gradient and the probability of an increase in deaths per million people can be detected from the fourth week. These results suggest that the presence of certain geographical features, such as hills, could prevent the virus from moving from one place to another within a district. Based on these results, we can infer that altitude and gradient could act as natural barriers to prevent the spread of pandemics throughout the country.

5. Conclusions

Understanding of the different factors that are conditioning the evolution of COVID-19 deaths could be key for designing preventative policies aimed at minimizing large-scale economic and social losses in this and future pandemics. Indeed, Casalino (2017) shows that during periods of epidemics, authorities and the population took specific measures to address the situation. These periods constituted opportunities to improve health conditions. Therefore, an understanding of the determinants of this pandemic can serve to improve health systems and to design programs so that the population and the government know how to act efficiently during similar emergencies in the future.

To this end, the present study seeks to contribute to the literature on the determinants of COVID-19 cases and deaths in Peru—specifically, the role of mobility, geography, and development. To this end, we employed Poisson regression with random effects and data from four groups of variables at the district level: (1) COVID-19, (2) mobility, (3) geographical variables, and (4)socioeconomic variables.

The results show that empirical relations change according to the evolution of the pandemic. On the one hand, we found that mobility had a negative relationship with the likelihood of an increase in COVID-19 cases and deaths during the first nine weeks of the pandemic but had a positive relationship starting in the eleventh week. On the other hand, we found that socioeconomic variables such as GDP per capita and life expectancy had positive associations with the probability of COVID-19 cases and deaths increasing; however, the magnitude of the empirical relationship decreases as the weeks progress. On the other hand, we found that geographical variables such as altitude and gradient have negative associations with the probability of COVID-19 cases and deaths increasing, but the statistical significance and the magnitude of the empirical relationship is not observed for any weeks of the pandemic. The results also reveal that the role of geographical and socioeconomic variables depend on the inclusion of Lima in the empirical analysis.

6. Implications, limitations, and future agenda

Our results have three main implications. First, they show that mobility raises the probability of an increase in COVID-19 cases and deaths from the eleventh week of the pandemic. In this regard, it is vital that the government find efficient ways of keeping social distancing in place so as to limit the number of people who travel more than one kilometer. Second, the results indicate that geographical and socioeconomic variables have important associations with the probability of an increase in COVID-19 deaths. Therefore, the government must implement measures to tackle the pandemic based on the level of risk in each region and their geographical and socioeconomic variables. Third, the figures that show the probability of a rise in cases and deaths per million people allow us to identify the departments in which the government must target its intervention during this or future pandemics.

Nonetheless, the study has several limitations. The first is that the geographical and socioeconomic variables included in the analysis have no temporal dimensions, and thus it is not possible to observe how they have varied from one day to the next. In this context, future studies could draw on "big data" sources to generate high-frequency economic indicators at the subregional level to analyze the dynamics of geographical and socioeconomic variables. Future studies could also include other geographical variables at the subregional level that have been used in some studies for aggregate country-level analysis (Henderson et al., 2020; Walrand, 2021). Among the geographical variables that could be included in future studies are latitude, temperature, humidity, precipitation, water flow, and air quality.

The second limitation is that we did not take into account health-sector variables. Thus, future research could incorporate variables that measure health system quality and provisioning in each region, including the number of doctors and nurses, intensive care beds, availability of medication, and so on. These variables could serve to identify whether the low death rates in some regions may be due to the performance of the health sector, or whether they have more to do with immunological factors that the population has developed through living in a certain location. Along these lines, it is also important to include indicators of genetic variation that the population has developed to acquire immunity from certain kinds of diseases, depending on the department in which they were born or live; this could help to manage future pandemics. The third limitation concerns the indicator of mobility used in this study: it does not allow a distinction to be drawn between individuals involved in pandemic-response roles and the rest of the population. Thus, future studies could devise separate indicators of mobility for the sectors involved in controlling the pandemic and for the rest of the economy. Future studies could also explore other ways of creating indicators of mobility for small administrative divisions (Chauvin, 2021; Couture et al., 2021; Cook, Currier, & Glaeser, 2022).

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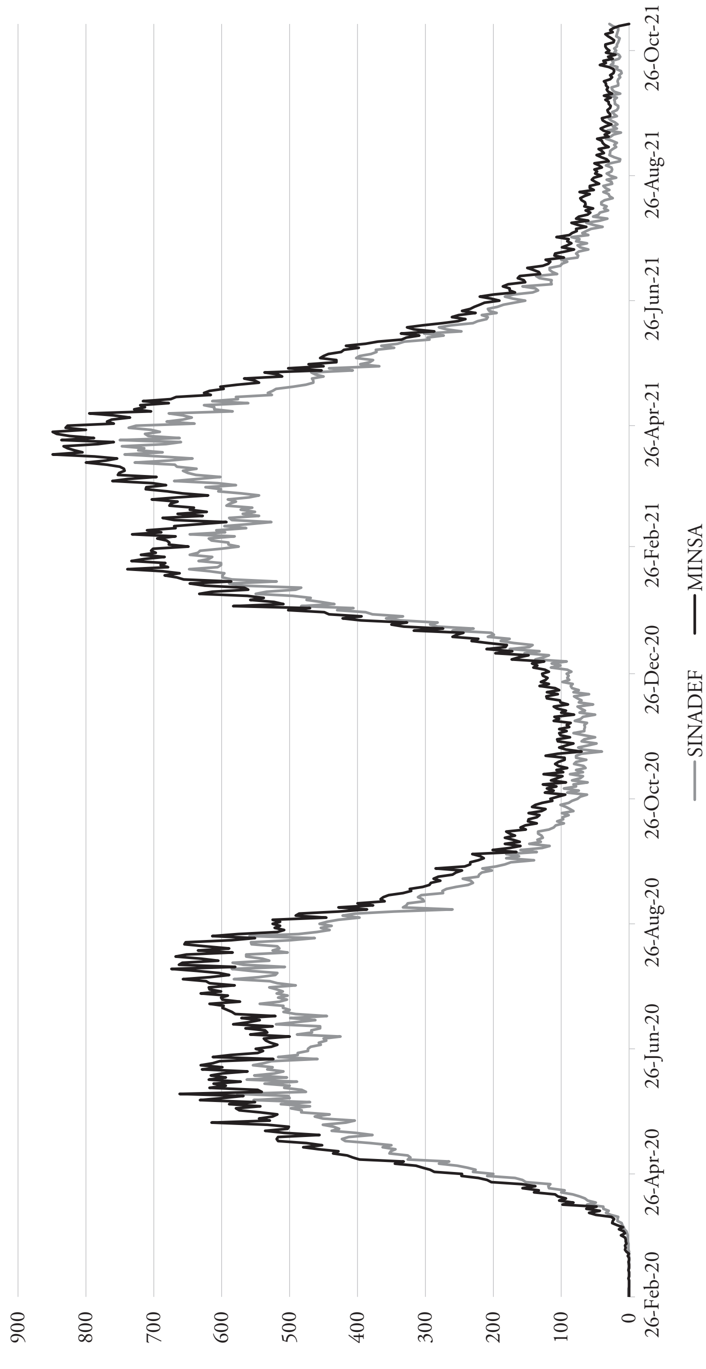
Appendix 1.
Evolution of deaths from COVID-19 in Peru, 2020-2021



Sources: Ministry of Health (MINSA) and National Information System on Fatalities (SINADEF). Compiled by authors.