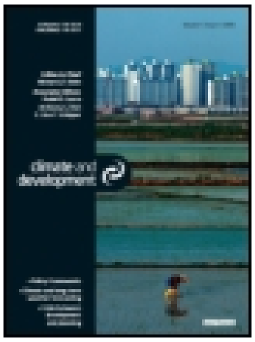

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RESEARCH ARTICLE

Disasters and economic growth: evidence for Argentina

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ABSTRACT

Disasters pose a serious threat globally. In this paper we estimate the impact of disasters on economic growth at the district level for Argentina, for the period 1992–2013. Due to the lack of disaggregated GDP data, night light maps reported by the United States' National Oceanic and Atmospheric Administration (NOAA) are used as a proxy for economic activity. Disaster information comes from the records of the Disaster Inventory System (DesInventar), which include the full range of disasters, from mild to severe ones. A regression analysis is carried out considering a panel of districts, linking luminosity with disasters.

We find that an additional disaster -weighted by its severity- is associated with a small though statistically significant reduction in the district's economic growth rate, specifically, of 0.53 percentage points in the year of its occurrence. This result is mainly driven by the impact of hydrological disasters. However, we find no evidence of persistence of this effect over time; on the contrary there seems to be a recovery in the following period. Given the methodological limitations due to data constraints, estimates found here probably constitute a lower bound of the true macroeconomic effect. Thus, further research on the topic is recommendable.

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Disasters; GDP; economic growth; night light luminosity; floods; earthquakes; Argentina

1. Introduction

In recent years, there has been increasing interest in examining the effect of the occurrence of disasters on the economic growth of affected areas.[1] This is the result of the increasing occurrence of disasters and their high economic costs. The empirical evidence has revealed mixed results. On the one hand, there is evidence of lower growth after a disaster (Noy, 2009; Strobl, 2011; Berlemann and Wenzel, 2016; Klomp and Valckx, 2014; Lazzaroni and van Bergeijk, 2014; IMF, 2018). On the other hand, there is also evidence of higher growth after disasters (Albala-Bertrand, 1993; Skidmore and Toya, 2002; Porcelli and Trezzi, 2018). In fact, different hypotheses on how economic activity might respond to disasters have been proposed in the literature, which support one or the other finding.

Hsiang and Jina (2014) detail the four possible trajectories that may occur over time. A disaster may cause a persistent reduction in growth, what is called the 'no recovery' hypothesis: the destroyed capital is replaced using resources that would otherwise be used for new productive investments, and no rebound occurs. A disaster may also cause only a temporary growth-reduction, which is subsequently overcome by a rebound[2], such that income levels converge back to the pre-disaster trend; this is the 'recovery to trend' hypothesis. Third, it is also possible that the replacement of destroyed capital with newer and much more productive capital fosters growth in such a way that it outweighs the initial loss; this is the 'build back better' hypothesis. Finally, there is the 'creative destruction' hypothesis, by which disasters may foster a faster economic growth due to an increase in the demand of goods and services to replace lost capital as well as inflow of international aid.

The vast majority of papers on the subject study the impact of major disasters across countries and over time. A smaller number of papers exploit differences at sub-national scale, either by provinces or districts, as this requires data on geographically disaggregated gross domestic product (GDP) series, which is quite scarce (Strobl, 2011; Anttila-Hughes and Hsiang, 2013; Boustan et al., 2020; Panwar and Sen, 2020). Papers studying impacts at disaggregated levels also find mixed results. Strobl (2011) reports that the occurrence of hurricanes in the United States, significantly reduces growth in affected districts (−0.45 percentage points). Coffman and Noy (2011) report similar results when analyzing the long-term impact of a large hurricane in districts of Hawaii, as well as Lima and Barbosa (2018) and Oliveira (2019), when examining the districts of two Brazilian provinces (Santa Catarina and Ceará, respectively). However, Noy and Vu (2010) find for the case of regions in Vietnam, that those disasters that destroy more capital and property boost economic activity in the short-run, as opposed to more lethal disasters, which result in lower output growth.

For the purposes of implementing prevention, mitigation and reconstruction policies, it is relevant to know the impact of disasters in different areas of a country, and how they are periodically affected by these events (Anees et al., 2020). This is especially true in the face of multiple disasters of limited

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geographic scope. That is, the economic impact derived from the periodic occurrence of the different types of disasters can be insignificant at the aggregate level, but it may cause a wide reduction in the economic activity of the affected areas. Thus, estimating the impact of disasters at a disaggregated scale is relevant for policy makers.The case of Argentina is relevant for studying the impact of disasters on economic activity because its vast territory and its diverse climates favour the periodic occurrence of multiple types of disasters. These include frequent floods in the northern and Center regions, earthquakes in Cuyo and the Northwest region, and snowfall and fires in the south, in the Patagonia region. In 2018, Argentina was among the 10 countries with the highest number of registered disasters (CRED, 2019).

However, in principle, a study of the effect of disasters on growth at a sub-national level would not be feasible in Argentina, as there are no official GDP estimates series at the provincial or district level. The most recent GDP estimates for provinces date back to 2004 (INDEC, 2005). Some private consultants have developed approximations to provincial GDP, such as the Synthetic Index of Provincial Activity of Muñoz et al. (2019) estimated from 2004 to present.

Trying to overcome the previous data constraints, which are frequent among developing countries, the use of various measures as proxies for GDP have been proposed. In particular, one that has obtained wide diffusion is the use of satellite images of night luminosity to estimate economic activity.

The National Oceanic and Atmospheric Administration (NOAA) of the United States -within the framework of the Defense Meteorological Satellite Program Operational Linescan System (DMSP/OLS)- periodically publishes the images of night-time lights from what is reported by different satellites, with information digitized since 1992.[3] This data-source offers a time series of more than two decades of night-time lights registry for the case of Argentina, with a high level of spatial disaggregation. Moreover, this kind of measurement reflects both formal and informal activities, something typically not incorporated in GDP measurements. Henderson et al. (2012), Chen and Nordhaus (2011) and Pinkovskiy and Sala-i-Martin (2015) find that night light is a good predictor of the GDP growth.

Precisely because luminosity is considered a proxy for economic growth, some studies analyse the relationship between disasters and economic growth approximated by luminosity records. In particular, Klomp (2016) finds that climatic and hydrological disasters significantly reduce nigh-time luminosity in affected areas of emerging countries; Bertinelli and Strobl (2013) find that hurricanes in the Caribbean reduce economic growth by 1.5% per year, estimated from luminosity data. Kohiyama et al. (2004) estimate the impact of disasters by measuring the affected area from the loss or reduction of luminosity immediately after the occurrence of the disaster.

In this paper we seek to estimate the impact of disasters on economic growth in Argentina. Since there is no data on economic growth at a disaggregated level, building on the aforementioned works, we use the nocturnal luminosity images provided by NOAA as a proxy for economic growth for the period 1992–2013 (the annual series was discontinued in 2013). The data on disasters comes from the DesInventar records. With these two data sources we construct a panel of districts of Argentina for an over 20-years period and conduct a regression analysis.

To the best of our knowledge, this work adds value to this literature in two ways. First, it is the first work that examines impact of disasters on growth for Argentina at the district level. Second, by considering the complete distribution of disasters -instead of only analysing those of great magnitude- this work provides new evidence on effects of less severe but frequent disasters. The results suggest a significant reduction in economic growth rate at the district level in the event of an additional disaster (0.53 percentage points) in the year of its occurrence.

The paper is organised as follows. Section 2 comments on the main antecedents in the use of luminosity images as a proxy for economic activity. Section 3 describes the methodology and sources of information used. Section 4 presents the main results and, finally, section 5 presents the conclusions.

2. Night light luminosity and economic activity

Night-light data has been extensively used as a proxy for economic activity on a national and subnational scale (Elvidge et al., 1997; Doll et al., 2000; Sutton and Constanza, 2002).[4] Elvidge et al. (1997) find a high correlation between GDP and luminosity for a group of 21 countries -including Argentina- from a regression analysis. Doll et al. (2000) and Sutton and Constanza (2002) additionally estimate the GDP per pixel on the map. In turn, Ebener et al. (2005) find a high correlation between luminosity and GDP per capita and advocate for night light as a good estimate of GDP and GDP per capita on a national and sub-national scale. However, the authors also warn that, given the saturation on the luminosity scale, luminosity could underestimate GDP per capita in small and densely populated territories (such as Monaco or Singapore).

More recently, Henderson et al. (2009, 2012) and Chen and Nordhaus (2011) have made contributions on the relationship between GDP growth and luminosity growth considering a wide panel of countries. Henderson et al. (2012) argue that, for predictive purposes, it is relevant to know how changes in luminosity are associated with changes in GDP/income (inverse of the elasticity of luminosity with respect to GDP) and propose the following equation (p. 1007):

$$z_j = \hat{\psi} x_j + e_j \tag{1}$$

where z_j is the variation (logarithmic difference) of GDP; x_j is the variation (logarithmic difference) of the night light and e_j is the error term. When estimating the previous equation, they obtain a coefficient of 0.28. Considering a more limited group of countries and incorporating fixed effects by country and year, Bertinelli and Strobl (2013) obtain a somewhat higher estimate (0.44) (p 1695). Other papers perform estimates on levels rather than on first differences. In particular, a log–linear specification –logarithm of the PBI vs. untransformed luminosity scale– is used in Ghosh et al. (2010, p. 148), while a log–log specification –logarithm of the GDP vs. logarithm of the luminosity scale– is implemented in

Sutton and Constanza (2002, p. 512) and Prakash et al. (2019, p. 15).

Luminosity maps have also been used in other topics. Without pretending to be exhaustive, some of its applications include its use for estimating population in urban settlements (Amaral et al., 2006), or estimating population density (Sutton et al., 1997); luminosity has also been used for constructing poverty maps on a global scale (Elvidge et al., 2009a), a regional scale (Noor et al., 2008) or national scale (Wang et al., 2012), as well as for detecting forest fires (Fuller & Fulk, 2000), among others.

The use of night light images has not been without criticism. First, not only human activity produces nocturnal luminosity capable of being detected from space; forest fires also generate luminosity. At the same time, clouds reduce the luminosity detected by the satellites, and days lasts longer in summer, reducing the time frame for night–light detection. Echoing the issue of clouds, NOAA publishes a series of cloud–free average stable luminosity, which is the one used in this paper. However, other issues remain.

In the period 1992–2013, a total of 6 satellites have provided luminosity images (identified as F10, F12, F14, F15, F16 and F18), and there is no official calibration of the information provided by these satellites, i.e. the luminosity maps of different satellites are not strictly comparable. Trying to overcome this limitation, several calibration methods have been proposed (Elvidge et al., 2009b; Li et al., 2012; Li and Zhou, 2017). In turn, Ayadi et al. (2018) suggest using the information of the oldest devise, which is what we do in this paper. Also, as already mentioned, the saturation of the luminosity scale (0–63) in certain urban areas is another limitation that may tend to underestimate the true differences in night–time luminosity (Ebener et al., 2005; Ghosh et al., 2013), reducing the correlation between this and socio–economic variables (Ma et al., 2014). In the next section we detail how we deal with these issues.

3. Methodology and data

3.1. Sources of information

We use three sources of information in this paper. In the first place, we use the night light records provided by NOAA (2014) for the period 1992–2013 as a proxy for economic activity (GDP) and its growth rate. These registers provide a luminosity scale of 0–63 (digital numbers based on radiance estimates). For each pixel on the map this scale ranges from 0 (minimum brightness) to 63 (maximum brightness), and each value has an accuracy of 30 arc seconds (equivalent to 1 km^2 close to equator). The 0–63 scale is defined by NOAA considering that each pixel stores data in 6 bits (2^6), that is, up to 64 positions.

In this paper we use the annual stable lights series provided by NOAA, which allows overcoming the limitations that arise from the presence of clouds or sporadic luminosity. In those years in which the luminosity information is available for more than one satellite, we use that from the oldest device in operation to preserve comparability over time, following the criteria of Ayadi et al. (2018). Similar to Falchi et al. (2016), the luminosity data is averaged by year (subscript t) and district (subscript d) –expression 2– using QGIS 3.4. We do not correct for saturation, as any of the districts reaches the maximum value of the luminosity scale at any point.[5] The limitations in the comparability of the information over time and across geographical units are also dealt with the inclusion of time fixed effects and district fixed effects correspondingly in the econometric model.

$$0 \leq L_{d,t} \leq 63 \qquad (2)$$

The mean value of the luminosity series is 12.06 (with a 95% Confidence Interval -CI- of 11.64-12.47). The districts with the highest average luminosity are those of the City of Buenos Aires and its suburbs. The simple correlation coefficient between luminosity and GDP for provinces (estimates of Muñoz et al. 2019) is 0.65, and it is in line with that reported in previous work (Ebener et al., 2005). The luminosity maps of Argentina at the district level are presented in Figure A.1 in the Annex.

In the second place, the district layer we use to create the luminosity district-measure from the NOAA information corresponds to that elaborated by the Integrated Public Use Microdata Series platform (IPUMS, 2017). These records are consistent with the 2010 Argentinean census microdata available on the same platform. IPUMS considers 350 districts (departments, parties or commune, depending on the province). We calculate the average of the luminosity scale of the pixels that cover the surface of each of the 350 districts.

In the third place, the information on disasters comes from the records of the Disaster Inventory System (DesInventar, 2018) prepared by the Social Studies Network on disaster prevention in Latin America (LA RED). We consider the occurrence of disasters in the period 1992–2013, coincident with the period with luminosity information.[6] These records are based on information extracted from newspapers of national circulation, especially La Nación and Clarín (Herzer et al., 2004).

It should be noted that for the Argentine case, disaster records are also available from the Emergency Events Database (EM-DAT), which contains information on more than 200 countries, prepared by the Center for Research on the Epidemiology of Disasters (CRED) of the Catholic University of Leuven. The EM-DAT records present several differences with those included in DesInventar. First, EM-DAT only provides information on major disasters. To be included in the base a disaster must meet at least one of the following conditions: having caused 10 or more deaths, affected 100 or more people, or required international aid or the declaration of a state of emergency (CRED, 2020). In contrast, DesInventar does not require minimum damage thresholds for the inclusion of disasters; as long as there is some social loss, the event is included. Second, EM-DAT offers a less disaggregated geographical reference of the occurrence of disasters (province), while DesInventar provides information at the district level. These differences make the DesInventar database a preferred source of information for this paper.

Table 1 presents the classification of disasters in Argentina, according to group and type, and their frequency of

Table 1. Number of records by type of disaster (1970–2015).

Disaster group	Type of disaster	Records	%
Hydrological	Flood	6997	44.41
Meteorological	Tempest	3117	19.78
Meteorological	Snowstorm	981	6.23
Climatological	Forestal fire	967	6.14
Climatological	Drought	680	4.32
Meteorological	Gale	626	3.97
Meteorological	Fog	508	3.22
Meteorological	Hailstorm	372	2.36
Climatological	Frost	370	2.35
Climatological	Heat wave	275	1.75
Meteorological	Rains	192	1.22
Geophysical	Alluvium	182	1.16
Geophysical	Earthquake	158	1.00
	Other[a]	331	2.10
	Argentine total	15756	100

Source: own elaboration based on DesInventar.

[a] Includes: volcanic activity, landslide, electrical storm, tornado, avalanche, storm surge, change of coastline and sedimentation. According to the Center for Research on the Epidemiology of Disasters (CRED), geological disasters are events that originate on solid earth; Meteorological disasters are events caused by short-lived, micro-to meso-scale extreme weather and atmospheric conditions that last from minutes to days; Hydrological disasters are events caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater; Climate disasters are events caused by by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability (Below et al., 2009).

occurrence for the entire period with available information. It is observed that floods and storms are the types of disaster with the highest number of records, with almost two-thirds of the total. Logically, they also have a broad participation in the records of mortality and affected people according to DesInventar.

Figure 1 depicts the distribution of disasters registered over the whole period covered by DesInventar database (1970-2013) and the number of deaths caused by them. It can be seen that a vast majority of Argentine districts present numerous records of disasters as well as deaths. Also, those districts of the Central region (Buenos Aires, Santa Fe and Córdoba) and the Northeast region (especially Formosa, Salta and Jujuy) tend to be the most severely affected.

Figure 2 depicts the temporal evolution of the number of disasters and deaths caused by them, exhibiting a wide variability in both series. However, of the ten years with the highest records of disasters, five correspond to the last decade (2007, 2008, 2009, 2006 and 2005).

3.2. Weighted disasters

To estimate the impact of disasters on economic activity, rather than considering the simple frequency of the occurrence of disasters, we weight them by their severity in two ways: by disaster-type and by individual severity. As DesInventar records present a large number of missing values in the indicators that would allow quantifying individual severity, weighting by disaster-type is a way of ameliorating the data limitations we face.

Let $e = 1, \ldots, E$ be each of the types of disasters that took place according to the DesInventar records – detailed in column 2 of Table 1. Let $z = 1, \ldots, Z_e$ be the number of disasters of each type. Let d be the subscript indicative of the district and t indicative of the year. To construct the accumulated weighted disasters variable A_{dt}, for each district d and year t, we proceed in three steps.

First, we define a specific weighting for each type of disaster W_e, which is a simple average between the proportion of total deaths registered by disasters between 1970-2015 that was attributed to disaster type e, denoted as M_e, and the proportion of total population exposed to disasters between 1970–2015 who were exposed to disaster type e, denoted as P_e.[7]

$$W_e = (M_e + P_e)/2 \tag{3}$$

Secondly, we define, for each district and year, a measure of severity by type of disaster, denoted as S_{edt}, given by the aggregate proportion of eight categories of infrastructure – included in the DesInventar records – that were affected by the disasters of each type e. The eight categories of infrastructure are: schools, hospitals, aid, transportation, communications, water network, sewer network, and electric network. The aid category refers to emergency response infrastructure such as

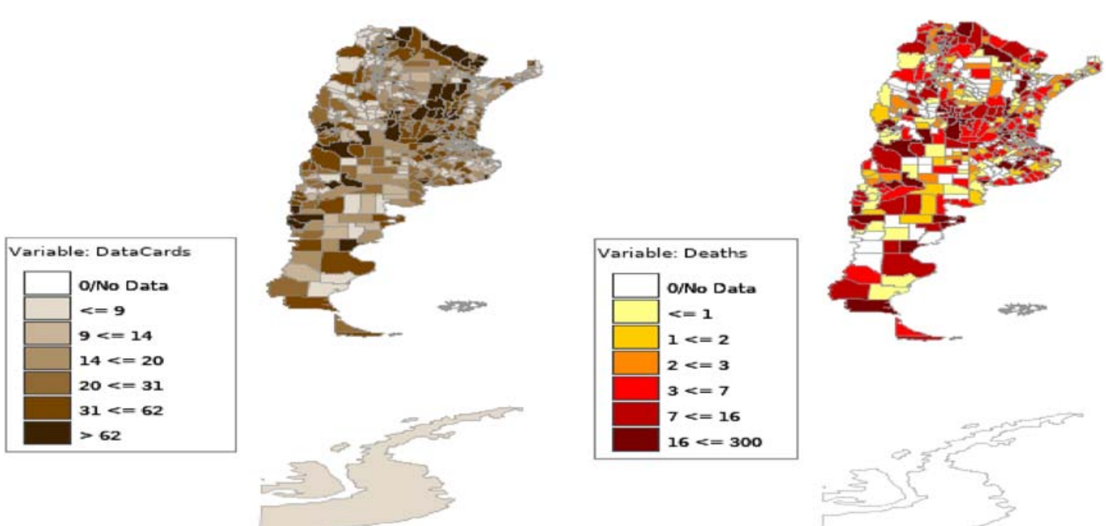

Figure 1. Number of disaster records (left) and number of deaths (right). Source: Own elaboration based on DesInventar. Note: All types of disasters registered by DesInventar are included in the graphs (1970–2015).

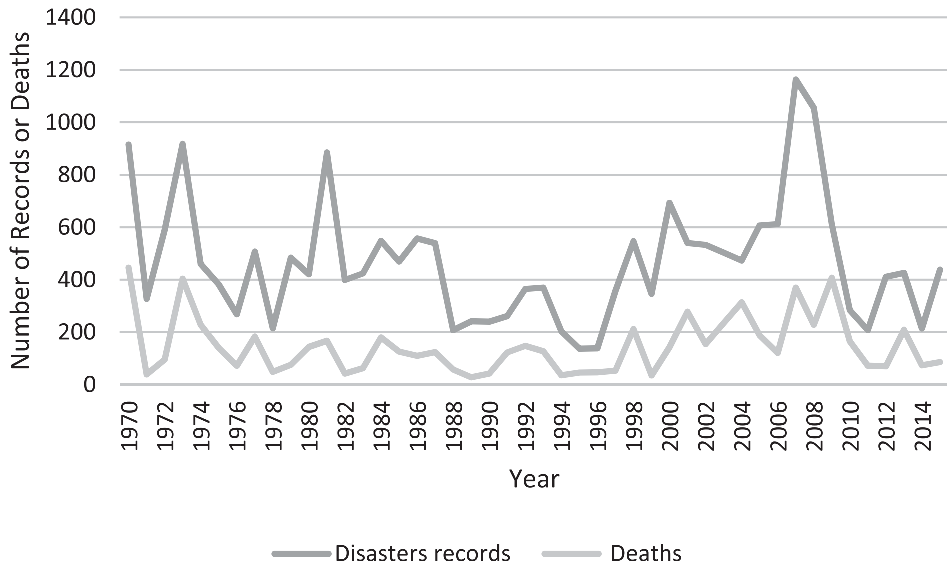

Figure 2. Temporal evolution of number of records and deaths. Source: Own elaboration based on DesInventar.

fire departments and civil defense. S_{edt} is given by:

$$S_{edt} = \sum_{i=1}^{8}\sum_{z=1}^{Z_e}\frac{\mathbb{I}(L^i_{edtz} > 0)}{8} \qquad (4)$$

where $\mathbb{I}(L^i_{edtz} > 0)$ is an indicator function that takes value 1 if the event z of type e (occurred in district d in year t) has caused damage to at least one element of that category of infrastructure, that is if $L^i_{edtz} > 0$, where L denotes 'loss', and takes the value 0 in the other cases.[8] We employ an indicator function of this type since numerous DesInventar records only indicate whether or not the particular event caused damage to some item in the category analyzed, without specifying the number of items damaged or the magnitude of the damage.

Finally, the weighted accumulated disasters variable A_{dt}, for each district d in year t, is defined as:

$$A_{dt} = \sum_{e=1}^{E} S_{edt} W_e \qquad (5)$$

Note that the double weight given by the product between the weight of each type of disaster and the specific severity of each individual disaster in each district and year introduces a greater degree of continuity in the definition. Descriptive statistics of this measure is provided in Table A.1 in Annex. The spatial distribution of the weighted accumulated disasters suggests that the districts of the City of Buenos Aires and its suburbs are the most affected by disasters. In the Results section we prove that the results are robust when excluding potential outliers in the measure of weighted disasters.

3.3. Empirical estimation strategy

Considering the sources of information detailed above, a panel of districts is constructed for the period 1992-2013. In particular, the relationship between economic activity and disasters is estimated from the following two-way fixed effects specification. This is consistent with the proposals of Deschenes and Greenstone (2011), Dell et al. (2012), Barreca et al. (2016) and Burke and Tanutama (2019).

$$l_{d,t,t-1} = \partial + \beta A_{d,t} + \gamma_d + \rho_t + \varepsilon_{d,t} \qquad (6)$$

where $l_{d,\,t,t-1}$ is the change in the logarithm of the average nighttime luminosity of district d between years t and $t\text{-}1$; $A_{d,t}$ is the number of weighted disasters that occurred in district d in year t; γ_d are district fixed effects and they try to control for those factors that are not observed and that differ between observational units; ρ_t are time fixed effects to control for potential comparability issues over time (Loayza *et al.*, 2012) and $\varepsilon_{d,t}$ is the error term of the model. The literature has also included infrastructure or human capital controls in the estimates (Toya & Skidmore, 2007; Yonson et al., 2018). However, this type of data is not available for the Argentine case with a disaggregation at the district level and with annual periodicity.

The above is our preferred specification since it achieves a high level of spatial disaggregation (district) and allows to build a panel of more than two decades with 350 observational units. We also show that the results are robust when considering a pooled regression, rather than a panel regression (Table A.5 in the Annex).

Since luminosity is only a proxy for product, as a robustness check we estimate a regression similar to equation (6) using the provincial GDP series produced by Muñoz and Asociados (2019), re–expressed in constant pesos using the GDP deflator series for Argentina published by the World Bank (World Bank, 2019). The relationship between GDP and disasters is estimated as:

$$y_{p,t,t-1} = \partial + \beta A_{p,t} + \gamma_p + \rho_t + \omega_{p,t} \qquad (7)$$

where $y_{p,t,t-1}$ is the change in the log of GDP of province p between years t and $t\text{-}1$. Fixed effects by province (γ_p) and year (ρ_t) are included. The model error term is $\omega_{p,t}$.

As another robustness exercise, equation 6 is re-estimated using two alternative specifications: a) considering as the dependent variable the luminosity level (not in differences) in logarithmic scale (equation 8), and b) considering as the dependent variable the luminosity level (not in logarithmic scale) (equation 9). Additionally, the estimate that considers the product at the provincial level is re-estimated excluding the City of Buenos Aires, which is the district with the highest per capita product and the largest number of disaster records. This exclusion responds to the fact that newspapers whose reports serve as a source for the DesInventar records are located in the City of Buenos Aires (Herzer *et al.*, 2004) and disasters registry may thus over-represent this district.

$$l_{d,t} = \partial + \beta A_{d,t} + \gamma_d + \rho_t + \varepsilon_{d,t} \tag{8}$$

$$L_{d,t} = \partial + \beta A_{d,t} + \gamma_d + \rho_t + \varepsilon_{d,t} \tag{9}$$

where $l_{d,t}$ is the logarithm of the average luminosity in district d in year t (equation 8) and $L_{d,t}$ is the average value of the luminosity scale (0-63) in district d in year t (equation 9).

4. Results

In Table 2 we present the estimation results of equation 6, that is, the relationship between the occurrence of disasters weighted by severity, and economic activity as measured by night-time light. Alternative specifications (equations 8 and 9) are also presented.

The results suggest a negative and significant relationship between disasters and economic growth in districts of Argentina. In effect, a unit increase in the number of weighted disasters is associated with a decrease of 0.53 percentage points in the growth rate -proxied by luminosity growth- in the year of the disaster. The alternative specifications coincide in sign and significance.

These results are lower in magnitude than those found elsewhere. Considering an unbalanced panel of 147 countries between 1992-2008, Klomp (2016, Table 3) reports much higher estimated coefficients, of between 1.3 and 2 points (Table 3). However, Klomp (2016) uses disaster data from EM-DAT records, which, as already mentioned, only considers severe disasters. In this paper, minimum damage conditions are not imposed for a disaster to be included. The differences in the magnitude of the coefficient may also be due to the inclusion of different controls as well as to the different definition of the regressor of interest: Klomp (2016) employs the number of disasters normalized by the surface of the country of occurrence.

Table 2. Growth and disasters in districts of Argentina (1992–2013).

Night light luminosity	Difference of logarithms (eq. 6)	Logarithms (eq. 8)	Level (eq. 9)
Disasters	−0.0053**	−0.0172***	−0.0829***
	(0.0026)	(0.0057)	(0.0302)
Intercept	0.0616	2.1062	14.1762
	(0.0052)	(0.0036)	(0.0523)
Fixed effects	Yes	Yes	Yes
Observations	7350	7700	7700
Groups	350	350	350

Note: robust standard errors *a la* Driscoll and Kraay (1998) in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3. Growth and disasters in Argentinean provinces (2004–2013).

	Difference of logarithms (eq. 7)	
GDP	Including Buenos Aires City (1)	Excluding Buenos Aires City (2)
Disasters	−0.00002***	−0.00002***
	(6.51e-06)	(6.37e-06)
Intercept	0.0711	0.0726
	(5.11e-06)	(4.66e-06)
Fixed effects	Yes	Yes
Observations	216	207
Groups	24	23

Source: own elaboration based on Muñoz *et al.* (2019) and DesInventar.
Note: robust standard errors *a la* Driscoll and Kraay (1998) in parentheses.
* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3 presents the results of alternative estimates for robustness checks. Column (1) corresponds to the estimation of equation 7 using data on provinces' GDP, including the 23 Argentinean provinces and the City of Buenos Aires. Column (2) repeats the estimates excluding Buenos Aires City.

The sign and significance of the estimates is preserved; however, the magnitude of the estimated impacts at the provincial level is lower: each additional disaster reduces the economic growth rate of the affected province by 0.002 percent points in the year the disaster occurred. However, it is intuitive to find a smaller effect at a provincial level as compared to the district level, as the effect of the disaster occurred in a specific district can be diluted when considering the GDP of the province. Also, at each moment in time, different number of disasters of heterogeneous severity can take place simultaneously in different districts of the same province, and thus the specific impact of the more severe ones can be reduced by the impact of less severe ones.

The results are also robust to multiple specifications. First, we consider the inclusion of lags of the dependent variable as regressors, as performed by Loayza *et al.* (2012). This implies considering a dynamic model controlling by the initial conditions. The disaster coefficient maintains its sign and significance in all the alternatives (see Table A.2 in Annex). Second, the results are also robust to excluding potential outliers both in terms of the number of weighted disasters (Table A.3 in Annex) and in night light luminosity (Table A.4 in Annex). Third, results are robust to considering a pooled regression, rather than a panel of districts (Table A.5 in the Annex). Fourth, the results are robust to considering the possibility of heterogeneous treatment effects following the proposal of Chaisemartin and D´Haultfceuille (2020), who re-estimate the weight of each observation considering its standard deviation for a two-way fixed effects model, as the one presented in this work (Table A.6 in the Annex).

So far it has been observed that disasters as a whole are associated with a mild growth reduction in Argentine provinces and districts in the year of occurrence. A natural question is which type of disasters have greater effects. Table 4 presents the results that arise from estimating equation 6 by group of disaster, following the classification proposed by DesInventar.

It is observed from Table 4, that geophysical disasters have the greatest negative effect on the economic growth of the affected districts, but significance is only at the 10% level. Hydrological disasters appear as the only ones with a

Table 4. Economic growth and disasters, in districts of Argentina, by type of disaster.

Night light luminosity	Geophysical	Meteorological	Climatological	Hydrological
Disasters	−0.3215*	−0.0020	0.0637	−0.0063**
	(0.1889)	(0.0094)	(0.0395)	(0.0030)
Intercept	0.0615	0.0615	0.0613	0.0618
	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Fixed effects	Yes	Yes	Yes	Yes
Observations	7350	7350	7350	7350
Groups	350	350	350	350

Source: own elaboration based on NOAA and DesInventar.
Note: robust standard errors *a la* Driscoll and Kraay (1998) in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5. Persistent impact of disasters on growth in districts of Argentina.

Night light luminosity	1	2	3	4
Disasters in *t*	−0.0055**	−0.0046*	−0.0046*	−0.0051*
	(0.0028)	(0.0026)	(0.0026)	(0.0029)
Disasters in *t-1*	0.0082***	0.0089***	0.0095***	0.0094***
	(0.0027)	(0.0028)	(0.0028)	(0.0028)
Disasters in *t-2*		−0.0065**	−0.0051	−0.0056*
		(0.0029)	(0.0032)	(0.0029)
Disasters in *t-3*			−0.0021	−0.0031
			(0.0028)	(0.0028)
Disasters in *t-4*				−0.0031
				(0.0028)
Fixed effects	Yes	Yes	Yes	Yes
Observations	7350	7000	6650	6300
Groups	350	350	350	350
R^2	0.1	0.1	0.13	0.11

Source: own elaboration based on NOAA and DesInventar.
Note: robust standard errors *a la* Driscoll and Kraay (1998) in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

significant effect at the 5% level. Presumably, the greatest negative impact of these two kinds of disasters occurs via the destruction of basic infrastructure.

Results from Table 4 are consistent with evidence on the impacts of disasters at the microeconomic level for Argentina. González et al. (2020) find that exposure to geophysical and hydrological disasters in the first months of life, significantly increases the chances of being poor in adulthood. The same is true in terms of lower educational attainment from exposure to hydrological disasters. These results arise from estimating a differences-in-differences model based on census microdata (2010) and DesInventar disaster records.

Finally, it is relevant to test the possible persistence of the effects of these disasters on growth. To do this, equation 6 is re-estimated including a lagged term for the number of weighted disasters; results are reported in Table 5.

Interestingly, although a negative and significant effect on growth is observed in the year of occurrence of the disaster, the effect becomes positive when considering its first lag. For subsequent lags, the effect is negative but non-significant (except for the second lag when only two lags are included).[9] These results seem to be in line with the predictions of neoclassical growth models. Given the destruction of a part of the capital as a consequence of the disaster, the hypothesis of recovery to trend is conceivable (Hsiang & Jina, 2014). That is, after the disaster there is a lower growth of the product associated to the destruction of physical and human capital. However, given the relative scarcity of capital in the affected region there is an inflow of capital that temporarily raises growth. Eventually the inflow of capital stops and growth returns to that corresponding to the steady state of the economy.

5. Conclusions

This paper has estimated the effect of the occurrence of disasters of all kinds and magnitudes on economic growth in Argentina at the district and provincial level, for the period 1992-2013. Building upon previous papers, in absence of disaggregated information on economic activity (GDP) at the district level, we have proxied this variable by information on night-time light captured by satellite images, provided by the United States' National Oceanic and Atmospheric Administration (NOAA). Information on disasters comes from the DesInventar database, which includes all kinds of disasters, from mild to severe ones. Combining these two data sources and using the district layer as defined by the Integrated Public Use Microdata Series platform (IPUMS, 2017) (which is consistent with the 2010 Argentinean Census), we construct a panel of 350 districts with information on disasters and night-time luminosity levels.

Estimating a fixed-effects model we find a negative and significant relationship between disasters and economic growth, as proxied by the difference of the logarithms of luminosity. Specifically, an additional weighted-disaster is associated with a reduction of 0.53 percent points in the luminosity growth rate of the district in the year of occurrence. This result is robust in sign and significance to a variety of robustness checks, such as using actual GDP estimates (rather than luminosity), which are available only at the provincial level, estimating a pooled regression, excluding extreme values either of the disasters or the luminosity distributions, including the lagged dependent variable, as well as considering heterogeneous treatment effects.

When disaggregating the impact of disasters by group, we find that it is actually hydrological disasters the ones with a significant negative effect on growth. Interestingly however, when exploring the persistence of the effect, we find that the negative effect is restricted to the year of occurrence of the disaster. In contrast, there is a positive effect on luminosity growth when considering disasters occurred in the previous year, and non-significant impacts of disasters occurred in earlier years. This is in line with the hypothesis of recovery of the growth-trend, as predicted by neoclassical growth models.

In sum, evidence found in this paper suggests a small but significant negative effect of disasters on economic growth -as proxied by growth in nigh-time light registers- in the district and in the year of occurrence, a result mainly driven by hydrological disasters. Yet, evidence also suggests that this negative effect could be overcome by growth in the following period. However, the results obtained here must be considered in light of the present methodological limitations.

First, the lack of detailed data on each specific disaster in the records of the Disaster Inventory System (DesInventar) could generate an underestimation of the true severity of disasters. Second, while the night-time luminosity registry was the best available proxy, it can clearly be a very imperfect one, especially for a country such as Argentina, highly dependent on primary activities, which may not have a high correlation with luminosity. Thus, it is essential to have disaggregated and updated information on economic activity in the Argentine case. This would allow testing the results found here with actual district-GDP estimates. Third, the consideration of spill-over effects between districts using spatial econometric techniques, could provide more accurate estimates of the effect of disasters.[10] In any case, considering that the estimates found here probably constitute a lower bound of the true macroeconomic effect, and that there is evidence of greater impact of disasters at the individual level in terms of human development variables (Gonzalez et al., 2020), it seems reasonable to promote investment in the prevention and mitigation of disasters.

Notes

1. There is also a broader literature which examines the impact of environmental shocks on different economic outcomes (Dell et al., 2012; Dell et al., 2014; Burke et al., 2015; Carleton & Hsiang, 2016; Hsiang *et al.*, 2017).
2. The rebound is fostered by a rise in the marginal product of capital, as capital and labour become relatively scarce after the disaster.
3. Luminosity data collection began in 1970 and was only declassified in 1972 (public access was allowed). However, from 1972 to 1992 the information was only available for consultation in physical records at the University of Colorado (Elvidge et al., 2001).
4. Previously, other papers have explored the relationship between night-time luminosity and aspects such as urbanizations or energy consumption (Croft, 1978; Welch, 1980; Foster, 1983).
5. No district, in any year, reaches the maximum value on the luminosity scale (63). In any case, it is shown that the results are robust to the exclusion of the districts with greater luminosity (Table A.4 in Annex).
6. However, DesInventar contains disaster records the period 1970-2015.
7. In this way, if, on average, for example, floods tend to be more severe than hailstorms, each flood record will receive a greater weighting and the lack of data in some individual records can be partially overcome.
8. For example, if a certain disaster (of type *e*, occurred in district *d* in year *t*) caused damage to at least one school, then $\mathbb{I}(L^i_{edtz} > 0) = 1$, for *i* = schools.
9. The analysis of lagged effects is scarce in the literature (Klomp & Valckx, 2014; Lazzaroni & van Bergeijk, 2014).
10. Also, as suggested by Okuyama (2009), there are other methodologies -namely Input-Output (IO) models and Social Accounting Matrix (SAM) models- that allow assessing the total impact of a disaster, (considering both first-order and higher order effects), which take into account the system-wide impact of flow losses through interindustry relationships. That would require much more detailed information on the impacts of each specific event.

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No potential conflict of interest was reported by the author(s).

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Annex

Table A.1. Descriptive statistics for weighted disaster measures.

Disaster measures	Mean	Standard deviation
A_{dt}	0.1136	0.6941
S_{edt}	0.2534	0.2307
We	0.0476	0.1252
M_e	0.0560	0.0751
P_e	0.0526	0.1992

Source: own elaboration based on DesInventar.

Table A.2. Growth and disasters in districts of Argentina (1992–2013) in a dynamic model.

Night light luminosity	Difference of logarithms (eq. 6)	Logarithms (eq. 8)	Level (eq. 9)
Disasters	-.0082**	-.0151***	-.0701**
	(.0036)	(.0057)	(.0290)
First lag of the dependent variable	.5036***	.4899***	.4965***
	(.0040)	(.1074)	(.1011)
Fixed effects	Yes	Yes	Yes
Observations	7000	7350	7350
Groups	350	350	350

Source: own elaboration based on NOAA and DesInventar.
Note: robust standard errors *a la* Driscoll and Kraay (1998) in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.3. Growth and disasters in districts of Argentina (1992–2013) excluding outliers in the distribution of weighted disasters.

Night light luminosity	Difference of logarithms (eq. 6)	Level of Logarithms (eq. 8)	Level (eq. 9)
Disasters	-.0630**	-.2054**	-2.1047***
	(.0276)	(.0896)	(.7260)
Intercept	.0404	2.1052	14.1146
	(.0105)	(.0045)	(.0228)
Fixed effects	Yes	Yes	Yes
Observations	6964	7275	7275
Groups	350	350	350

Source: own elaboration based on NOAA and DesInventar.
Note: robust standard errors *a la* Driscoll and Kraay (1998) in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. Those observations whose weighted number of disasters were above the 95th percentile of the weighted disaster distribution were excluded.

Table A.4. Growth and disasters in districts of Argentina (1992–2013) excluding outliers in the distribution of luminosity.

Night light luminosity	Difference of logarithms (eq. 6)	Level of Logarithms (eq. 8)	Level (eq. 9)
Disasters	-.0035**	-.0178***	-.0872***
	(.0019)	(.0059)	(.0333)
Intercept	.0620	2.0078	11.6539
	(.0076)	(.0035)	(.0118)
Fixed effects	Yes	Yes	Yes
Observations	6982	7315	7315
Groups	350	350	350

Source: own elaboration based on NOAA and DesInventar.
Note: robust standard errors *a la* Driscoll and Kraay (1998) in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. Those observations that are located above the 95th percentile of the luminosity distribution, in each specification, are excluded.

Table A.5. Growth and disasters in districts of Argentina (1992–2013) in a pooled regression.

Night light luminosity	Difference of logarithms (eq. 6)	Level of Logarithms (eq. 8)	Level (eq. 9)
Disasters	-.0054**	-.0172***	-.0729***
	(.0025)	(.0055)	(.0301)
Intercept	.0427	4.4743	54.9059
	(.0104)	(.0316)	(.1889)
Fixed effects	Yes	Yes	Yes
Observations	7000	7350	7350

Source: own elaboration based on NOAA and DesInventar.
Note: robust standard errors in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.6. Growth and disasters in districts of Argentina (1992–2013) with heterogeneous treatment effects.

Night light luminosity	Difference of logarithms (eq. 6)	Logarithms (eq. 8)	Level (eq. 9)
Disasters	-.0276*	-.0177***	-.1719***
	(.0148)	(.0019)	(.0042)
N	4856	5126	5126

Source: own elaboration based on NOAA and DesInventar.
Note: standard errors in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. Estimates obtained using the package *did_multiplegt* in STATA.

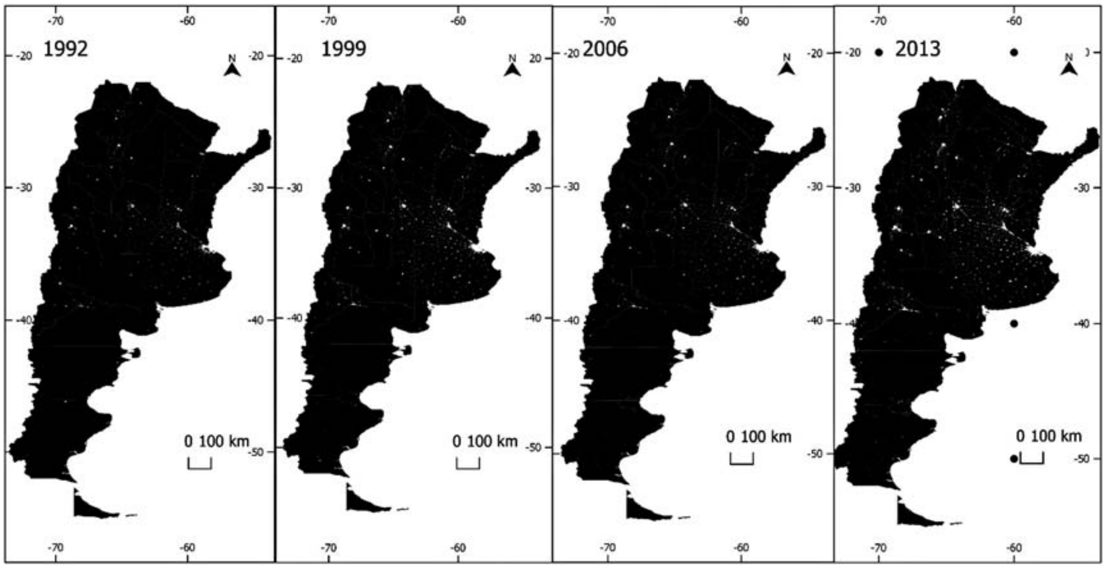

Figure A.1. Night light maps for Argentina, selected years
Source: own elaboration based on NOAA