The Death Effect of Severe Climate Variability

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<td>As Published</td>
<td><a href="http://dx.doi.org/10.1016/S2212-5671(13)00024-5">http://dx.doi.org/10.1016/S2212-5671(13)00024-5</a></td>
</tr>
<tr>
<td>Publisher</td>
<td>Elsevier B.V.</td>
</tr>
<tr>
<td>Version</td>
<td>Final published version</td>
</tr>
<tr>
<td>Accessed</td>
<td>Sat Dec 29 11:32:09 EST 2018</td>
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<tr>
<td>Citable Link</td>
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International Conference on Applied Economics (ICOAE) 2013

The death effect of severe climate variability

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Abstract

Using data for all 2,454 municipalities of Mexico for the period 1980-2010, this paper analyzes the relationship between exposure to extreme temperatures and mortality rates. I find that severe heat increases mortality, while the health effect of severe cold is generally trivial. I show that exchanging one day with a temperature of 16-18 °C for one day with temperatures higher than 30 °C increases the crude mortality rate by 0.15 percentage points, a result robust to several model specifications. It is also found that the extreme heat effect on death is significantly more acute in rural regions, leading to increases of up to 0.2 percentage points vis-à-vis a 0.07-point increase in urban areas.

Keywords: climate extremes, mortality, Mexico.

1. Introduction

The mechanisms through which weather impacts human welfare are complex and rarely linear. In addition, they often encompass a wide variety of factors ranging from geographical location, economic development, settlement patterns and behavioral adaptation to intra-seasonal acclimatization, demographic characteristics, urbanization, and environmental pollutants. Inherent features of the developing world make people residing in industrializing regions more exposed to the negative impacts of weather than their developed-world counterparts. On average, people in developing countries spend more time outdoors (Basu and Samet, 2002), whether at their workplace, producing goods for their household’s own use and maintenance, commuting, or even carrying out activities to meet biological needs such as eating, sleeping, and relaxing. Even indoors,

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households in developing countries are more likely to lack air conditioning or display other features providing insulation from extreme weather (Rothman and Greenland, 1998).

In developing settings specifically, the welfare impact of weather can be generally understood as the extent to which climate impacts human physiology, both through thermal stress and changes in metabolic rates, as well as increased incidence of diseases caused or spread by severe climatic conditions. In an extreme situation, these negative impacts may ultimately lead to death. In fact, the effect of extreme weather on mortality is a public health threat of considerable magnitude: even though economic (including insured) disaster losses associated with climate and geophysical events are higher in developed countries, fatality rates are higher in developing countries. During the period from 1970 to 2008, over 95 percent of deaths from inclement weather occurred in developing countries (IPCC, 2012.)

Substantial epidemiological evidence documents a strong relation between severe weather and morbidity and mortality. The body adapts thermally to survive in drastic temperature environments, typically through thermoregulatory control mechanisms, such as shivering, arteriovenous shunt vasoconstriction, sweating and precapillary vasodilation in cold and hot environments, respectively. But these physiological processes are only effective within certain limits. Weather can be so extreme that such adjustments fail to balance body and ambient temperature, which in turn leads to strokes, hypothermia and hyperthermia, and other conditions that may be fatal.

Many studies focusing on both industrial and developing countries have consistently shown that extreme heat is a natural hazard that can have a pronounced effect on human wellbeing. This relationship has been considered relevant to public health for millennia and empirically researched as early as the 1930s: in a classic study, Gover (1938) reports excess deaths associated with elevated ambient temperature exposure in 86 U.S. cities from 1925 to 1937. Studies of army recruits published in the 1940s (Schickele, 1947) and 1950s (Stallones, Gauld and Dodge, 1957) also underscore an association between ambient heat exposure and death. More recently, Hajat, O’Connor and Kosatsky (2010) observe that in Europe, increases in emergency hospital admissions among individuals with respiratory diseases have been noted during hot weather, while in studies from the United States, heat-related increases were noted in admissions for heart disease, acute myocardial infarction, and congestive heart failure. Using district-level data for India, Burgess et al. (2011) show that hot days and deficient rainfall cause large increases in mortality within a year of their occurrence in rural regions. Basu and Samet (2002) and Kovats and Hajat (2008) present a general review of the literature on the effects of hot temperature on mortality rates.

Evidence is also robust for cold climate. Deschênes and Moretti (2009) estimate that the aggregate effect of cold weather on mortality is quantitatively large, the number of annual deaths attributable to cold temperature being equivalent to 0.8 percent of total deaths in the United States. This effect is even larger in low-income areas. Hashizume et al. (2009) characterize the daily temperature-mortality relationship in rural Bangladesh and find that for the period between 1994 and 2002, a 1°C decrease in mean temperature was associated with a 3.2 percent (95 percent confidence interval: 0.9–5.5) increase in mortality, with deaths resulting from perinatal causes sharply increasing with low temperatures. In an international study of temperature and weather in urban areas using data from 12 cities in developing countries, including Mexico City and Monterrey, McMichael et al. (2008) find a U-shaped temperature-mortality relationship, with significant death rate increases at lower temperatures. Analitis et al. (2008) study the short-term effects of cold weather on mortality in 15 European cities and find that a 1°C decrease in temperature was associated with a 1.3 percent increase in the daily number of total natural deaths and increases of 1.2 percent, 1.7 percent and 3.3 percent in cerebrovascular, cardiovascular and respiratory deaths, respectively, the increase being greater for the older age groups. Hassi (2005) presents a review of the literature on cold exposure mortality.
2. Empirical Strategy and Data Construction

I propose an empirical approach that estimates the effect of weather on human physiology, particularly on death. First, I discuss the data I use and then the methodology employed to carry out the empirical analysis.

2.1. Data

An empirical specification that captures the relationship between weather and mortality, thus illustrating the human impact of weather, requires data on two types of variables: one that operationalizes human physiology, and one that operationalizes climate.

To calculate mortality rates, information on deaths, births, and population are needed. I obtained death and birth counts data at the municipal level through each state’s Civil Registry Office. Since each state has its own registration data and formats, I digitized and harmonized the 32 datasets (31 state datasets and one dataset for Mexico City) using standardized codes for births, deaths, and fetal deaths. I collected monthly data for the period January 1990-December 2010 for 2,454 Mexican municipalities (99.9 percent of the total.) Given that annual population data are not available in Mexico, I constructed a population monthly time series using censal information for population in combination with migration flow data obtained from Mexico’s National Council of Population Demographic Indicators and the State and Municipal Database System of Mexico’s National Institute of Statistics (INEGI.) These data are available for years 1990, 1995, 2000, and 2010. For intercensal years, I estimated (midyear) population using the component method, which is defined by the use of estimates or projections of births, deaths, and net migration to update a population (Hollmann et al., 2000.)

With these variables, I constructed a crude (total) mortality rate, which I define as the total number of deaths per period per 1,000 people. In addition to the crude mortality rate, I also distinguish among two subtypes of mortality indicators: infant mortality rate (i.e., the number of deaths of children less than 1 year old per period per 1,000 live births); and fetal mortality rate (i.e., the number of stillbirths per period per 1,000 live births). I also compare these mortality rates by area, defining the rural mortality rate as the mortality rate in communities with fewer than 2,500 residents, and urban mortality rate as the mortality rate in communities with 2,500 residents or more. Of particular relevance is the comparative analysis of urban and rural areas, given that rural regions mostly rely on agriculture for subsistence, and the primary sector is highly vulnerable to extreme weather fluctuations. Table 1 presents relevant descriptive statistics.

Table 1. Mortality Rates in Mexico, 1990-2010, by Type of Area

<table>
<thead>
<tr>
<th></th>
<th>Pooled (1)</th>
<th>Rural (2)</th>
<th>Urban (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude mortality rate</td>
<td>4.8</td>
<td>9.1</td>
<td>4.9</td>
</tr>
<tr>
<td></td>
<td>(1.4)</td>
<td>(34.5)</td>
<td>(1.9)</td>
</tr>
<tr>
<td>Infant mortality rate</td>
<td>15.4</td>
<td>31.6</td>
<td>19.8</td>
</tr>
<tr>
<td></td>
<td>(9.6)</td>
<td>(160.3)</td>
<td>(64.9)</td>
</tr>
<tr>
<td>Fetal mortality rate</td>
<td>10.5</td>
<td>16.4</td>
<td>13.6</td>
</tr>
<tr>
<td></td>
<td>(6.7)</td>
<td>(99.6)</td>
<td>(51.5)</td>
</tr>
</tbody>
</table>

Note: Municipalities may consist of urban areas only, rural areas only, or a combination of both. All statistics are weighted by total municipal population. Standard deviations in parentheses.

The ultimate essential data to carry out any empirical analysis on weather and its impacts are, of course, climatic records. There is a variety of models that provide environmental analysts with climatic observations and some have been employed to assess weather impacts in Mexico in terms of human, environmental, and agricultural outcomes. In studying the impact of severe weather on health and cognitive development, Aguilar
and Vicarelli (2011) use precipitation data at 0.5 degree resolution climate grids, which were generated by the Climate Research Unit and the Tyndall Centre for Climate Change Research, both at the University of East Anglia. Sáenz Romero et al. (2010) develop spatial climate models to estimate plant-climate relationships using thin plate smoothing splines of ANUSPLIN software, created by the Australian National University. Pollak and Corbett (1993) use spatial agroclimatic data to determine corn ecologies.

The underlying problem with these and other works that follow similar methodologies is their use of monthly climatic data. Using monthly climatic data is problematic due to the nonlinear effects of weather, which may be concealed when, for example, daily observations are averaged into monthly or seasonal variables. In effect, daily and even finer-scale weather data facilitate estimation of models that aim to identify nonlinearities and breakpoints in the effect of weather. Using daily temperature data, Schlenker and Roberts (2009) find a nonlinear asymmetric relationship between weather and crops yields in the United States, with yields decreasing more rapidly above the optimal temperature vis-à-vis their increasing below the optimal temperature. The assumption of nonlinearity is particularly critical for studies like this one, where the researcher attempts to represent the relationship between weather and human physiology. In many studies, for the case of mortality, a J-or U-shaped curve has been found appropriate to describe the association, with elevated mortality being observed at temperature extremes and relatively lower mortality at moderate temperatures (Burgess et al., 2011; Curriero et al. 2002; Deschênes and Greenstone, 2011; Huynen et al., 2001; Kunst, Looman and Mackenbach, 1993.)

For this paper, I use daily temperature and precipitation data from the North American Regional Reanalysis (NARR) model (NOAA, 2012.) The NARR project is a long-term, high-frequency, dynamically consistent meteorological and land surface hydrology dataset developed by the National Centers for Environmental Prediction (NCEP) as an extension of the NCEP Global Reanalysis, which is run over the North American Region. It covers 1979 to 2010 and is provided eight times daily, on a Northern Hemisphere Lambert Conformal Conic grid with a resolution of 0.3 degrees (32km)/45 layers at the lowest latitude. In addition to the modeling benefits of high spatial resolution, I chose to work with the NARR due to the model’s good representation of extreme weather events, resulting from the model outputting all “native” (Eta) grid time-integrated quantities of water budget. Mesinger et al. (2006), for instance, compare the NARR precipitation for January 1998 (when the El Niño effect was underway) with observed precipitation. Their comparison shows that over land there is an extremely high agreement between NARR and observed precipitation, even over the complex western topography of Mexico.

Daily temperature and precipitation data were constructed in two simple steps. First, a spherical interpolation routine needs to be applied to the data: I took weighted averages of the daily mean temperature and accumulated precipitation of every NARR gridpoint within 30 kilometers of each municipality’s geographic center, with the inverse squared haversine distance between the NARR gridpoint and the municipality centroid as the weighting factor. Second, all the (365, or 366 for leap years) daily temperature estimates in a given year are distributed over 14 ranges or bins: daily mean temperature lower than 10°C; daily mean temperature higher than 30°C, and 10 two-degree-wide ranges (i.e., 10°C-12°C, 12°C-14°C,…, 28°C-30°C) in between. Similarly, the daily accumulated rainfall estimates are distributed over 15 two-millimeter-wide ranges (i.e., 0-2mm, 2-4mm,…, 28-30mm) plus an extra bin for daily accumulated precipitation exceeding 30mm, and another bin containing exclusively days without rainfall. The binning of the weather data is important for the empirical strategy that will follow, for it would maintain weather variation in any given specification, thus accounting for the nonlinear effects of weather extremes discussed above.

Table 2 summarizes the descriptive statistics for the temperature and precipitation variables employed.
Table 2. Relevant agricultural outcomes in Mexico, 1979-2009, by Type of Area

<table>
<thead>
<tr>
<th>Rates</th>
<th>Pooled (1)</th>
<th>Rural (2)</th>
<th>Urban (3)</th>
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</thead>
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<tr>
<td>Daily mean temperature (°C)</td>
<td>18.5</td>
<td>17.4</td>
<td>18.5</td>
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<tr>
<td></td>
<td>(4.4)</td>
<td>(3.9)</td>
<td>(4.4)</td>
</tr>
<tr>
<td>Annual average rainfall (mm)</td>
<td>712.8</td>
<td>678.9</td>
<td>713.0</td>
</tr>
<tr>
<td></td>
<td>(419.1)</td>
<td>(332.7)</td>
<td>(419.5)</td>
</tr>
<tr>
<td>Annual degree-days (over 30°C)</td>
<td>11.6</td>
<td>6.8</td>
<td>11.6</td>
</tr>
<tr>
<td></td>
<td>(45.5)</td>
<td>(30.0)</td>
<td>(45.5)</td>
</tr>
<tr>
<td>Annual degree-days (below 10°C)</td>
<td>30.1</td>
<td>38.7</td>
<td>30.1</td>
</tr>
<tr>
<td></td>
<td>(54.7)</td>
<td>(57.8)</td>
<td>(54.7)</td>
</tr>
<tr>
<td>Annual millimeters-days (over 8mm)</td>
<td>174.8</td>
<td>129.3</td>
<td>175.1</td>
</tr>
<tr>
<td></td>
<td>(225.1)</td>
<td>(139.8)</td>
<td>(225.4)</td>
</tr>
<tr>
<td>Annual millimeters-days (below 3mm)</td>
<td>779.7</td>
<td>764.9</td>
<td>779.8</td>
</tr>
<tr>
<td></td>
<td>(122.7)</td>
<td>(120.6)</td>
<td>(122.8)</td>
</tr>
</tbody>
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Note: If fewer than 2,500 residents live in a given municipality, such a municipality is considered “rural.” All statistics are weighted by total municipal population. Standard deviations in parentheses.

2.2. Empirical strategy

The empirical specification I employ to establish the relationship between weather and mortality is an attempt to capture the full distribution of annual fluctuations in weather based on the following equation:

$$Y_{mt} = \sum_{j=1}^{12} \theta_j tempbin_{mj} + \sum_{k=1}^{17} \rho_k rainbin_{mk} + \alpha_m + \gamma_t + \lambda_r t + \lambda_r^2 t^2 + \epsilon_{mt}$$

(1)

They should also be separated from the surrounding text by one space.

where $Y_{mt}$ is the log (crude or an alternative) mortality rate in municipality $m$ in year $t$ (for the sake of clarity, my analysis is carried out using logs.) $tempbin_{mj}$ and $rainbin_{mk}$ are the separate temperature and precipitation bins described above for municipality $m$ in year $t$. The impact of temperature thus equals the sum of all $j$ bins, whereas the impact of precipitation is equivalent to the sum of all $k$ bins. Notice that the only functional form restrictions in this specification are i) that the mortality impacts of temperature and precipitation are constant within each 2-degree and 2-millimeter range, respectively, and ii) that all days with temperatures/rainfall above (below or equal to) 30°C/30mm (10°C/0mm) have the same impact in terms of mortality.

$\alpha_m$ is the fixed effect of municipality $m$. Including municipality fixed effects controls for the average differences across municipalities in any observable or unobservable predictors of log mortality rate, so that, say, demographic, socioeconomic, or clinical impacts will not be confused with that of weather. Similarly, $\gamma_t$ is the unrestricted time fixed effect of year $t$. These fixed effects control for time-varying differences in the dependent variable that are common across municipalities, such as the introduction of the Seguro Popular in 2003. Because such shocks are unlikely to have the same effect at the regional level (for instance, among Seguro Popular delegations, the pricing of prescription drugs varies greatly across regions), equation (1) also includes quadratic polynomial time trends $\lambda_r$ for the $r=5$ mesoregions of Mexico (Northeast, Northwest, South, Center, and Center-West) which, at least in terms of weather, are fairly homogenous. Finally, $\epsilon_{mt}$ is the stochastic error term.

As discussed by Burgess et al. (2011) and Deschênes and Greenstone (2011), the validity of my empirical
strategy for studying the weather-mortality relationship relies on the assumption that equation (1) yields unbiased estimates of the \( \theta_j, \rho_k, \beta, \delta, \varphi \) and \( \eta \) vectors. Given the two-way fixed effect identification strategy employed, any omitted variables that are constant over time and/or particular to one municipality will not bias the estimates, even if the omitted variables are correlated with the explanatory variables. If weather variability is supposed to be random, then it is plausible to assume it is uncorrelated to unobserved mortality determinants. Because observing a common variance structure over time is unlikely, my results are based on a cluster-correlated Huber-White covariance matrix estimator, which avoids the assumption of homoskedasticity (Wooldridge, 2004.) In addition, my empirical specification is weighted by the square root of the total municipal population, in an effort to correct for heteroskedasticity associated with municipal differences in estimation precision of mortality rates, having the additional advantage of presenting impacts on one person, rather than one municipality (Deschênes and Greenstone, 2011).

3. Results

Figure 1 presents the results of the impact of temperature on mortality rates. More specifically, it shows the estimated impact of an additional day in 12 temperature ranges, relative to a reference range, which in this case is the 16\(^{\circ}\)C-18\(^{\circ}\)C range. Precipitation impact estimates are not reported as they were typically insignificant at conventional levels.

![Figure 1. Estimated impact of a day in 12 temperature bins on log annual mortality rate, relative to a day in the 16\(^{\circ}\)C-18\(^{\circ}\)C bin](image)

Two patterns emerge. First, notice that, graphically, a J-shaped curve is fairly appropriate to describe the weather-death association. As theory predicts, moderate temperature ranges do not seem to have an impact on mortality rates. In fact, among the eight bins that account for temperatures between 12\(^{\circ}\)-26\(^{\circ}\)C, only two are statistically significant at the conventional levels. Colder ranges in general do not have an effect statistically different from the reference bin. Second, extreme hot weather does seem to have a sustained impact on death. All three bins including the hotter temperature ranges are statistically different from the reference category. For instance, one additional day with an average temperature above 26\(^{\circ}\)C increases mortality rates by at least 0.1 percent relative to a day with a mean temperature in the 16\(^{\circ}\)-18\(^{\circ}\)C range.

As I pointed out before, some studies have investigated the impact of extreme weather on perinatal and infant mortality. Hashizume et al. (2009) find that perinatal mortality sharply increases with low temperatures. Dadvand et al. (2011) conclude that extreme heat was associated with a reduction in the average gestational
age of children, which is associated with perinatal mortality and morbidity. Burgess et al. (2011) show that weather extremes appear to increase infant mortality in rural India, but not in urban areas. Scheers-Masters, Schootman and Thach (2004) find no evidence that elevated environmental temperatures have a significant role in the development of sudden infant death syndrome.

Figures 2 and 3 show that there is no clear relationship between weather, either extreme or moderate, and fetal mortality. If anything, colder temperatures seem to be associated with lower fetal mortality rates, but the effect is minimal. All the temperature ranges above 12°C are small in magnitude and insignificant. As for infant mortality, extreme heat is positively associated with infant mortality rates, but in terms of extreme cold, it is not possible to reject the null of equality with the base category. It is noteworthy to mention that the point estimate of days with temperatures higher than 30°C relative to the reference 16°-18°C bin is 0.15 percent for the crude mortality response function, while it is 50 percent larger (0.23 percent) for the infant mortality specification. This finding echoes Deschênes and Greenstone’s (2011) result that the impact on annual mortality of hot weather (i.e., higher than 90°F) for infants is twice as large as the point estimate for the general population. The impact of precipitation on both fetal and infant mortality is, with frequency, statistically nil.
Figures 4 and 5 show the relationship between weather and death by type of area. I analyze two types of areas: rural and urban. Recall that I define rural mortality rate as the mortality rate in communities with fewer than 2,500 residents, and urban mortality rate as the mortality rate in communities with 2,500 residents or more. It is important to emphasize that this differentiation is relevant because it would indicate that people living in rural areas are potentially more exposed to the negative impacts of weather, given that their main economic activity, agriculture, is easily upended by climate shocks.

![Figure 4](image_url) Estimated impact of a day in 12 temperature bins on log annual urban mortality rate, relative to a day in the 16°-18°C bin

![Figure 5](image_url) Estimated impact of a day in 12 temperature bins on log annual rural mortality rate, relative to a day in the 16°-18°C bin

From the analysis of these plots, several interesting findings emerge. In terms of temperature, the effect on death is virtually zero for urban areas: only two out of the 12 temperature bins are significant, but small in magnitude, with no temperature bins being associated with increases in mortality rates greater than 0.1 percent. Conversely, the response function between log rural mortality rate and temperature indicates that rural areas are especially vulnerable to the negative effects of extreme (particularly hot) temperatures. Although the variance of rural mortality is high (see Table 1), which results in wider confidence intervals, the five hottest temperature bins (i.e., temperatures higher than 26°C) are all statistically significant and of higher
magnitude than the urban coefficients. For example, exchanging a single day in the 16°C-18°C range for one in the >30°C range would lead to an increase in annual mortality rates of 0.2 percent in rural areas (for urban areas the coefficient is not statistically different from the reference bin.) In terms of the precipitation response functions, with the exception of a couple of bins, for all the coefficients, both for urban and rural areas, it is not possible to reject the null of equality with the base temperature/precipitation bin.

4. Conclusion

Extreme weather exerts negative effects on humans, particularly on the most vulnerable. Using data for all the 2,454 municipalities of Mexico for the period 1980-2010, I analyzed the impact of exposure to severe weather, here defined as extreme temperatures and precipitation, on death.

I present empirical evidence for the hypothesis that extreme weather increases mortality rates. In particular, I find that extreme heat is the most damaging form severe weather may take. I find that extremely hot temperatures increase mortality. As expected, given that Mexico does not have harshly cold seasons, I do not find any statistically significant effect of cold weather on health. I find that precipitation extremes have an ambiguous effect on mortality depending on the model specification.

I find that rural areas are substantially more vulnerable to severe weather than urban areas. This echoes the conclusion of Burgess et al. (2011) for their study in India. As they put it: “quasi-random weather fluctuations introduce a lottery in the survival chances of citizens. But this lottery only affects people living in the rural parts where agricultural yields, wages and prices are adversely affected by hot and dry weather” (p. 34.)

These results have an important policy implication: technically speaking, the problem is one of missing markets rather than market failure. If regions specialized in agriculture (usually rural communities) had sufficient insurance and credit mechanisms catering to the poor, these would provide safety nets in the event of a weather shock. As a result, the government may play a key role in creating the conditions to mitigate the adverse effects of climate, even though these risks cannot be fully eliminated.

Furthermore, if extreme heat is the most lethal mechanism through which weather affects human physiology, and this impact is considerably stronger in rural regions, given their dependence on agriculture, the consequences of climate change are likely to be unevenly distributed across communities. There is empirical evidence that there has been an overall decrease in the number of cold days, while the number of warm spells and heat waves has increased (IPCC, 2012.) As a result, development policy must encompass differential vulnerability and capacity mechanisms in order for communities to better adapt to these changing conditions. Future research should focus on these environmental and institutional aspects.

Acknowledgements

I thank Karen Polenske, Carlos Ludeña and Sebastián Miller for valuable suggestions, as well as Esther Duflo and Dave Donaldson for fruitful discussions. I also thank Daniel Olguín for his MATLAB coding support, as well as NOAA for granting me access to NARR.

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