# Supplementary Materials for

## Impact of Temperature and Relative Humidity on the Transmission of COVID-19: A Modeling Study in China and the U.S.

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#### **Materials and Methods**

#### **Fama-MacBeth Regression with Newey-West Adjustment**

Fama-MacBeth regression is a way to study the relationship between the response variable and the features in the panel data setup. Particularly, Fama-MacBeth regression runs a series of crosssectional regressions and uses the average of the cross-sectional regression coefficients as the second step of parameter estimation. In equation form, for  $n$  response variables,  $m$  features and time series length  $T$ 

$$
R_{i,1} = \alpha_1 + \beta_{1,1}F_{1,i,1} + \beta_{2,1}F_{2,i,1} + \cdots + \beta_{m,1}F_{m,i,1} + \epsilon_{i,1},
$$
  
\n
$$
R_{i,2} = \alpha_2 + \beta_{1,2}F_{1,i,2} + \beta_{2,2}F_{2,i,2} + \cdots + \beta_{m,2}F_{m,i,2} + \epsilon_{i,2},
$$
  
\n
$$
\cdots
$$
  
\n
$$
R_{i,T} = \alpha_T + \beta_{1,T}F_{1,i,T} + \beta_{2,T}F_{2,i,T} + \cdots + \beta_{m,T}F_{m,i,T} + \epsilon_{i,T}.
$$

where  $R_{i,t}$ ,  $i \in \{1,\ldots,n\}$  are the response values,  $\beta_{k,t}$  are first step regression coefficients for feature k at time t, and  $F_{k,i,t}$  are the input features of feature k and sample i at time t. In the second step, the average of the first step regression coefficient,  $\beta_k$ , can be calculated directly, or via the following regression

$$
\beta_{k,t} = c_k + \epsilon_t.
$$

where  $\epsilon_t$  is the random noise.

Since  $\beta$ s might have time-series autocorrelation, in the second step, we thus use the Newey-West approach [1] to adjust the time-series autocorrelation (and heteroscedasticity) in calculating standard errors. Specifically, for the second step, we have

 $E[\epsilon] = 0$  and  $E[\epsilon \epsilon'] = \sigma^2 \Omega$ .

The covariance matrix of  $c_k$  is

$$
V_{C_k} = \frac{1}{T} \left(\frac{1}{T} \mathbf{1}' \mathbf{1}\right)^{-1} \left(\frac{1}{T} \mathbf{1}'(\sigma^2 \Omega) \mathbf{1}\right) \left(\frac{1}{T} \mathbf{1}' \mathbf{1}\right)^{-1},
$$

where **1** is a  $T \times 1$  vector of 1 and  $\sigma^2 \Omega$  is the covariance matrix of errors.

The middle matrix can be rewritten as

$$
Q = \frac{1}{T} \mathbf{1}'(\sigma^2 \Omega) \mathbf{1}
$$

$$
= \frac{1}{T} \sum_{i=1}^T \sum_{j=1}^T \sigma_{ij}
$$

The Newey-West estimators give a consistent estimation of  $Q$  when the residuals are autocorrelated and/or heteroscedastic. The Newey-West estimator can be expressed as

$$
S = \frac{1}{T} \left( \sum_{t=1}^{T} e_t^2 + \sum_{l=1}^{L} \sum_{t=l+1}^{T} w_l e_t e_{t-l} \right),\,
$$

where  $w_l = 1 - \frac{l}{1+l}$ , e represents residuals and L is the lag.

We use Fama-Macbeth regressions for two reasons. First, the temperature and relative humidity series have trends with the arrival of summer and the *R* value series also has downward trends. In this case, panel regression will obtain spurious regression results from the time-series perspective. However, the cross-sectional regression involving cities (counties) of various meteorological conditions and COVID-19 spread intensities will not have spurious regression issues. Second, Fama-MacBeth regression is valid even in the presence of cross-sectional heteroskedasticity (including complex spatial covariance) because in the second-step regression, only the value of the first step estimates  $\beta$ s are used, not their standard errors. Therefore, as long as the first-step estimator is unbiased, which is the case for heteroskedasticity (including complex spatial covariance), the Fama-MacBeth estimation is correct.

Less rigorously speaking, we use the first step of Fama-MacBeth regression to determine the extent to which the transmissibility of the areas of high temperature and high relative humidity are compared with that of low temperature and low relative humidity areas each day. We then use the second step to test whether daily relationships are a common fact during a given time period.

### **Estimating the Effective Reproduction Number**

The basic reproduction number *R<sup>0</sup>*, which characterizes the transmission ability of an epidemic, is defined as the average number of people who will contract the contagious disease from a typical infected case in a population where everyone is susceptible. When an epidemic spreads through a population, the time-varying effective reproduction number  $R_t$  is of greater concern. The effective reproduction number *Rt*, the *R* value at time step *t*, is defined as the actual average number of secondary cases per primary case cause[2].

We then calculate the effective reproductive number  $R_t$  for each city through a time-dependent method based on maximun likelihood estimation (MLE)[3]. The inputs to the method are epidemic curves, *i.e.*, the historical numbers of patients in each day, for a certain city. Specifically, we denote  $w(\tau|\theta)$  as the probability distribution for the serial interval, which is defined as the time between symptom onset of a case and symptom onset of her/his secondary cases. Let  $p_{(i,j)}$  be the relative likelihood that case *i* has been infected by case *j*, given the difference in time of symptom onset  $t_i - t_j$ , which can be expressed in terms of  $w(\tau | \theta)$ . That is, the relative likelihood that case *i* has been infected by case *j* can be expressed as

$$
p_{ij} = \frac{w(t_i - t_j)}{\sum_{i \neq k} w(t_i - t_k)}
$$

The relative likelihood of case *i* infecting case *j* is independent of the relative likelihood of case *i* infecting any other case *k*. The distribution of the effective reproduction number for case *i* is

$$
R_i \sim \sum_j \text{Bernoulli}[p_{(j,i)}]
$$

With the expected value

$$
E(R_i) = \sum_j p_{(j,i)}
$$

The average daily effective reproduction number  $R_t$  is estimated as the average over  $R_t$  for all cases *i* who develop the first symptom of onset on day *t*.

The above calculation is implemented with the package 'R0' developed by Boelle & Obadia with R version 3.6.2 and 'R0' version 1.2\_6 [\(https://cran.r](https://cran.r-project.org/web/packages/R0/index.html)[project.org/web/packages/R0/index.html\)](https://cran.r-project.org/web/packages/R0/index.html).

#### **Modeling Spatial Effect**

We use a generalized linear mixed model (GLMM) with spatial random effects to account for spatial autocorrelation between cities or counties in each cross-sectional regression. The form of the model is

$$
y=X\beta+u+\epsilon,
$$

where **y** is the  $N \times 1$  outcome vector, **X** is the  $N \times p$  matrix of the p explanatory variables (the intercept term can be included by setting the first column of X as a vector of ones),  $\beta$  is the vector of regression coefficients,  $\boldsymbol{u}$  is the vector of spatial random effects, and  $\boldsymbol{\epsilon}$  is the random error vector whose entries are independent and identically distributed as  $N(0, \sigma^2)$ . We assume  $\boldsymbol{u} \sim$  $N(0, \sigma_s^2 G)$ , where  $\sigma_s^2$  is the spatial variance and G follows a Matérn correlation structure[4].

The Matérn model flexibly specifies the correlation between any two cities or counties as a function of their geographical distance; the model has two parameters, a scale parameter  $\rho$  and a "smoothness" parameter  $\nu$ , and it subsumes the exponential and squared exponential models as special cases. The maximum likelihood method is used for parameter estimation[5].

We have also tried a conditional autoregressive model (CAR)[6] in which the spatial correlation is described by an adjacency matrix of the cities/counties. The Matérn model performs better than the CAR model as judged by the Akaike information criterion (AIC); the average AIC value across all cross-sectional regressions is 896.9 and 936.5 for the Matérn model and the CAR model, respectively.

All computations are performed in the R package "spaMM" version 3.3.0[7]. We report the results from the Matérn model in Table S9 and S10.



#### **Fig. S1. Estimation of the serial interval with the Weibull distribution**

Bars denote the probability of occurrences in specified bins, and the red curve is the density function of the estimated Weibull distribution.

#### **Table S1. Data Summary**

This table summarizes the variables used in this paper. Panel A and B summarize the data of Chinese cities and the U.S. counties.



#### **Panel B: Data Summary for the U.S. Counties**



#### **Table S2: Pairwise Correlation Analysis for Chinese Cities**

Pairwise correlation coefficients are obtained by averaging all correlation coefficients from each time step in the Fama-Macbeth approach.



### **Table S3: Pairwise Correlation Analysis for the U.S. Counties**

Pairwise correlation coefficients are obtained by averaging all correlation coefficients from each time step in the Fama-Macbeth approach.



#### **Table S4: Unit Root Test for R, Temperature and Relative Humidity**

Panel A and B show the results of Handri LM test [8] with null hypotheses of non-unit-roots, for Chinese cities and the U.S. counties, respectively.



## **Table S5: Coefficients of temperature and relative humidity in first step of Fama-Macbeth Regression**

Panel A and B show regression coefficients of temperature and relative humidity in the first step of Fama-Macbeth regression, for Chinese cities and the U.S. counties, respectively.

ranel A: Regression Coemicients for Chinese Crues		
Date	<b>Coefficient of Temperature</b>	<b>Coefficient of Relative Humidity</b>
Jan, 19	$-0.0373$	$-0.0109$
Jan, 20	$-0.0064$	0.0009
Jan, 21	$-0.0127$	$-0.0093$
Jan, 22	$-0.0309$	$-0.0121$
Jan, 23	$-0.0427$	$-0.0066$
Jan, 24	$-0.0249$	0.0010
Jan, 25	$-0.0238$	$-0.0062$
Jan, 26	$-0.0506$	$-0.0174$
Jan, 27	$-0.0526$	$-0.0159$
Jan, 28	$-0.0196$	$-0.0063$
Jan, 29	$-0.0340$	$-0.0101$
Jan, 30	$-0.0305$	$-0.0096$
Jan, 31	$-0.0391$	$-0.0087$
Feb, 1	$-0.0388$	$-0.0102$
Feb, 2	$-0.0248$	$-0.0097$
Feb, 3	$-0.0108$	$-0.0022$
Feb, 4	$-0.0091$	0.0020
Feb, 5	0.0039	0.0040
Feb, 6	$-0.0061$	$-0.0037$
Feb, 7	$-0.0034$	0.0006
Feb, 8	0.0103	$-0.0030$
Feb, 9	$-0.0077$	$-0.0067$
Feb, 10	$-0.0150$	0.0052

**Panel A: Regression Coefficients for Chinese Cities** 



#### **Panel B: Regression Coefficients for U.S. Counties**



#### **Table S6: Fama-Macbeth Regression for Chinese Cities except Wuhan**

Daily *R* values from January 19 to February 10 and the average temperature and relative humidity over 6 days up to and including the day when *R* value is measured, are used in the regression for 99 Chinese cities (without Wuhan). The regression is estimated by the Fama-MacBeth approach.







## **Table S7: Relationship between Temperature, Relative Humidity, and** *R* **Values: Robustness Check with the Serial Interval of Mean 7.5 Days and Standard Deviation 3.4 days in Li et al (2020)[2] for Chinese Cities**

This table utilizes the estimated serial interval in a previous paper (mean 7.5 days, std 3.4 days)[2] to construct *R* values for China. The table reports the coefficients of the effective reproductive number, *R* values, on an intercept, temperature, relative humidity and control variables in the Fama-MacBeth regressions.







## **Table S8: Relationship between Temperature, Relative Humidity, and** *R* **Value: Robustness Check with the Serial Interval of Mean 7.5 Days and Standard Deviation 3.4 days in Li et al (2020)[2] for the U.S. Counties**

This table utilizes the estimated serial interval in a previous paper (mean 7.5 days, std 3.4 days)[2] to construct *R* values for the U.S. counties. The table reports the coefficients of the effective reproductive number, *R* value, on an intercept, temperature, relative humidity and control variables in the Fama-MacBeth regressions.







## **Table S9: Relationship between Temperature, Relative Humidity, and** *R* **Value: Robustness Check with a social distancing dummy variable for the U.S. Counties.**

U.S. states lifted stay-at-home orders, namely a series of social distancing policies, at different times. This table shows the regression results for the U.S. Counties with an additional dummy explanatory variable recording whether the state where a county is located already lifted a stay-athome order. The regression is estimated by the Fama-MacBeth approach.







## **Table S10: Relationship between Temperature, Relative Humidity, and** *R* **Value: Robustness Check with spatial random effect of Chinese cities.**

Spatial random effects are introduced in first step of Fama-Macbeth regression to account for spatial correlation. The neighborhood structure is calculated from the Earth distances between cities.







## **Table S11: Relationship between Temperature, Relative Humidity, and** *R* **Value: Robustness Check with spatial random effect of the U.S. counties.**

Spatial random effects are introduced in first step of Fama-Macbeth regression to account for spatial correlation. The neighborhood structure is calculated from the Earth distances between counties.







#### **References**

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