When is the COVID-19 Pandemic Over? Evidence from the Stay-at-home Policy Execution in 106 Chinese Cities

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Abstract. As more and more countries have employed stay-at-home policy to halt the spread of COVID-19, the effectiveness of this policy has become an important question to both researchers and policymakers. To answer this question, our paper empirically measures the effect of stay-at-home policy on the control of COVID-19. Using the city-level Baidu Mobility Index, measured by the total number of outside travels per day divided by the resident population, we find that reducing the number of outings can effectively decrease the new-onset cases; a 1% decline in the outing number will reduce about 1% of the new-onset-cases growth rate in 7 days (one serial interval). The critical level is a *50% drop in mobility*, in which case the number of new-onset cases is lower than it was 7 days before, and hence the epidemic will gradually disappear holding this policy long enough. *A strong stay-at-home policy execution with a short duration has a smaller economic cost than a loose execution with a long duration.* For example, the mobility in Wuhan is down 85% after lockdown, in which case we estimate the number of new-onset cases is reduced by 50% in only 12 days.

Keywords: COVID-19, Stay at home, Baidu Mobility Index, Movement restriction

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The novel coronavirus disease 2019 (COIVD-19)[1, 2], first identified in Wuhan December 2019, was considered as an ongoing pandemic by the World Health Organization (WHO).[1] As of 23 March, 192 countries have reported more than 340,000 cases of COVID-19 and more than 14,000 deaths.[2] Worldwide outbreaks of COVID-19 have posed a huge obstacle to the international public health systems, financial markets and the global economy[3].

To stop the spread of the plague, many countries (including China, Italy and other European countries)[3] have imposed homestay policies to prevent personal contacts throughout the country, and asked people self-quarantine in epidemic-affected areas. However, different countries have different duration and tightness of this policy. For example, Prime Minister Giuseppe Conte has asked 60 million Italian citizens to stay at home for 25 days.[4] California's governor issued a statewide "stay at home" order to residents on March 19, asking them to go out only when necessary during the COVID-19 pandemic for 16 days.[5] Indian Prime Minister Narendra Modi has announced a complete travel restriction in the entire country for 21 days.[6]

The duration of the policy is certainly related to the tightness of policy execution, however, up to now, no research has empirically investigated the effect of stay-at-home policy on the control of novel coronavirus, and the relationship between the tightness and policy duration. Although movement restriction is commonly believed to be an effective way of blocking the transmission of the coronavirus[4, 5], previous literature mainly investigates the lockdown of Wuhan city via mathematical models[6, 7, 8, 9] or limited to qualitative analysis[10, 11].

We fill this gap by measuring the degree of policy execution on reducing the new-onset cases of COVID-19 using a sample of 106 Chinese cities during the COVID-19

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[1]Refer to "WHO Director-General's opening 7remarks at the media briefing on COVID-19 – 11 March 2020". World Health Organization. 11 March 2020. Retrieved 11 March 2020.

[2]https://www.worldometers.info/coronavirus/countries-where-coronavirus-has-spread/

[3]https://en.wikipedia.org/wiki/2019–20_coronavirus_pandemic#Self-isolation

[4]https://www.abc.net.au/news/2020-03-10/italy-travel-ban-extends-to-whole-country-due-to-coronavirus/12041262

[5]https://www.channelnewsasia.com/news/world/covid19-california-governor-issues-statewide-stay-at-home-order-12559238

[6]https://zeenews.india.com/india/india-locked-down-completely-for-next-21-days-to-fight-coronavirus-covid-19-announces-pm-modi-2271436.html

epidemic period in China. After the announcement of stay-at-home policy in China on January 23 and 24, when Wuhan was locked down and the first-level response to major public health emergencies in all Chinese provinces was announced, different Chinese cities have implemented this policy at various tightness levels. With the help of within-city Baidu's Mobility Index (BMI), measured by the total number of outside travels per day divided by the resident population, we can analyze empirically the effect of stay-at-home policies on the spread of COVID-19 across different Chinese cities. Certainly, the tightness of stay-at-home policy is inversely related to the BMI, more outside travels indicate a looser policy implementation.

We obtain the BMI from the Baidu Migration Map (https://qianxi.baidu.com/) for January and February 2020 in this paper. Figure 1 shows the BMI of 106 cities across China on January 22 and February 10, respectively. Although the BMI on February 10 is much lower than that on January 22, we can still see a big variance across different Chinese cities.

[Figure 1 about here.]

We also construct the epidemic curves, i.e. the historical numbers of patients with symptom onset of each day, for these 106 cities. Figure 2 shows the BMI averaged cross 106 cities weighted by the total number of cases as of March 9 from January 10 to February 20 together with the Chinese epidemic curve. With the introduction of stay-at-home policies on January 23 and 24, 2020, China's overall mobility has declined from 5 in the normal days until it reached its lowest point (about 1) on February 6, and has remained basically at this level since then, it is about an 80% drop! As mobility declines, so does the number of new-onset cases, from about 4000 cases per day before the implementation of the policy to about 500 cases per day on February 20. There is an increase in new-onset cases in China in the first few days of the implementation of the stay-at-home policy, because these new cases are infected before the implementation of the stay-at-home policy due to the relatively long COVID-19's incubation period.

Note that the BMI had fallen before the policy was implemented on January 23, likely due to the spontaneous non-out of the residents, as Professor Nanshan Zhong pointed out in a television interview on January 20 that the disease can transmit human-to-human. There is a spike on February 1 on the epidemic curve, we suspect that many people cannot remember their exact symptom-onset dates, but rather a rough period (e.g. early February), these onset dates are, therefore, recorded to be February 1. Given this, we, later on, do a robustness check by removing the observations on February 1.

[Figure 2 about here.]

Assuming the infected patients get the coronavirus from the virus carrier in a serial interval, defined as the time span between symptom onset dates of a primary case to the following case, we investigate the impact of a certain day's mobility situation (measured by BMI) on the growth rate of new-onset cases in a serial interval. Note that the growth rate of the new-onset cases can also be considered as the number of infected people per coronavirus carrier (deducted by 1) in a serial interval, thus, a measure of the intensity of coronavirus transmission. Certainly, if a strict stay-at-home policy is enforced, and no one goes on the streets, the number of onset cases after a serial interval will be significantly reduced. Therefore, the key idea of this paper is to *use the BMI to predict the growth rate of new symptom-onset cases in a serial interval*. Note that Wang, Tang, Feng and Lv (2020)[12] and Li, Q. et al (2020)[13] estimate a similar average serial interval, which is about 7 days, we, therefore, use 7 days as the length of the serial interval in our study.

As there are trends in both BMI and epidemic curves in nearly all Chinese cities, direct time-series regressions cannot be implemented, we, hence, use the Fama-Macbeth method[14] with Newey-West adjustment[15] on the standard errors. Particularly, on each day from January 24 to March 24, we perform a cross-sectional regression of predicting the growth rate of the new-onset case number, and take the mean of these regression coefficients as our estimate of the BMI influence on the new-onset-case growth rate. Table 1 shows that the movement restrictions play a strong role in reducing the number of new-onset cases at a 1% significance level, even after controlling for several other variables. Particularly, as shown in column one of Table 1, the new-onset-case growth rate in a serial interval decreases 18% if the BMI declines 1 point, which corresponds to a 20% drop of the normal mobility level. For example, if the travel level is as usual (about 5), the new-onset-case growth rate is about 50% in a serial interval in China; however, if the travel index level drops to 0.7 (85% drop), just like that in Wuhan City, the new onset case number can be *reduced* by 33% after a serial interval. The critical point of the BMI is 2.5 (about 50% of the normal mobility level), below which the growth rate of new case number will be less than zero, i.e., the new onset case number will be smaller than that a serial interval before, and hence the epidemic will gradually disappear holding this policy long enough.

[Table 1 about here.]

Turning to the control variables, the relative humidity (with a t-statistics of -1.6) and temperature (with a t-statistics of -0.5) show a negative influence on the growth rate of COVID-19. Since many people have to stay at home due to movement restriction, weather, therefore, is much less effective than that under natural conditions shown in Wang, Tang, Feng and Lv (2020)[12].

Next, we calculate the half-life horizon, defined as the time span for the new-onset-case number to be one half of the original, for different levels of BMI using the model (1) or (2) in Table 1. Half-lives certainly relate to the tightness of implementation of the stay-at-home policy and directly affect the duration of this policy. If a city strictly enforces the stay-at-home policy, its BMI will certainly be quite small, so the number of new-onset cases will drop at a fast speed, therefore, that city's stay-at-home policy does not have to be executed too long. On the contrary, if a city implements the policy loosely, it will certainly have a long execution period to halt the spread of the coronavirus. Figure 3 shows the convex-shape downward sloping curve between the half-lives and the tightness of movement restrictions. For example, the half-life is as long as 53 days for a BMI level of 2, a 60% decline compared to the normal level. If the BMI is 1 (80% decline from the normal level), as the average level in China for most of the time in February, the half-life is 15 days, which means that the new-onset-case number is only about 25% as one month before. Wuhan has implemented a quite restricted stay-at-home policy with a BMI of only 0.7, which corresponds to a half-life of 12 days, which means after 36 days of implementation, the new-onset-case number will shrink to only 12% of the number before the policy.

[Figure 3 about here.]

It is natural to assume that the economic loss of 1% mobility drop per day is fixed, for simplicity, we assume it to be 1, then the economic loss of halving the new-onset-case number is the product of the size of mobility drop and its corresponding half-life. Figure 4 shows that the economic loss falls with mobility drops, which informs that strong stay-at-home policy execution with a short duration has a smaller economic loss than a loose execution but with a long duration.

[Figure 4 about here.]

Overall, the stay-at-home policy is a commonly-used policy choice to halt the COVID-19 epidemic, we wish the analysis of this paper can add value for different countries and regions in choosing the policy tightness and duration that suits them.

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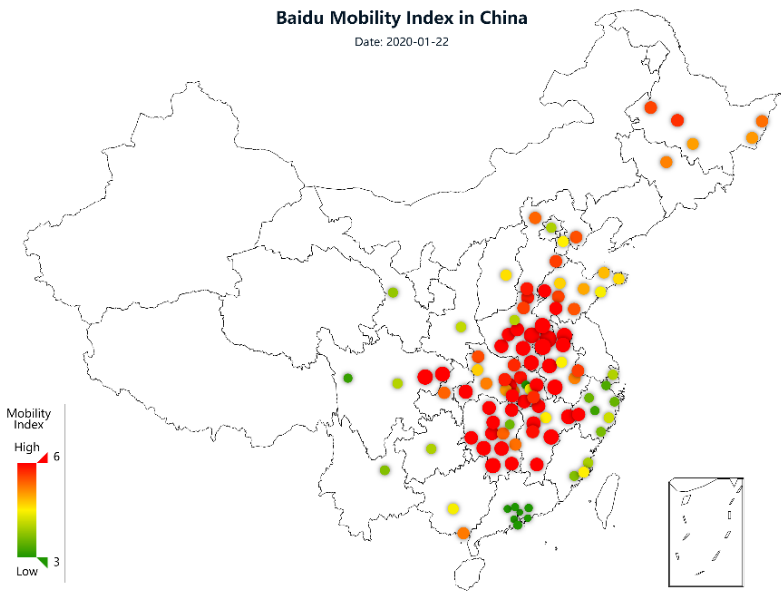
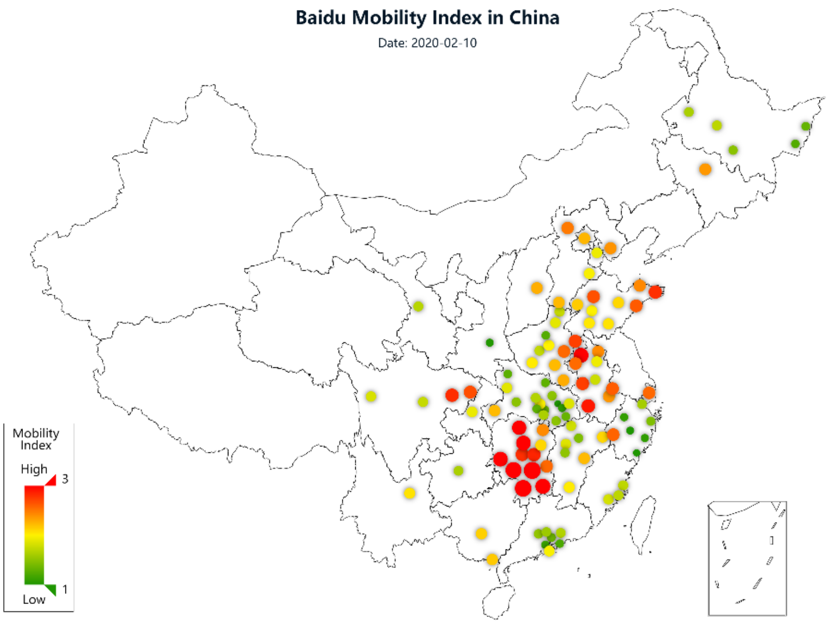


(a)



(b)

Figure 1: Baidu Mobility Index before and during the stay-at-home period in China

The Baidu Mobility Indexes for 106 cities in China are plotted on January 22 (before the stay-at-home policy) and February 10 (during the stay-at-home policy), respectively. There are large mobility variation cross different Chinese cities.

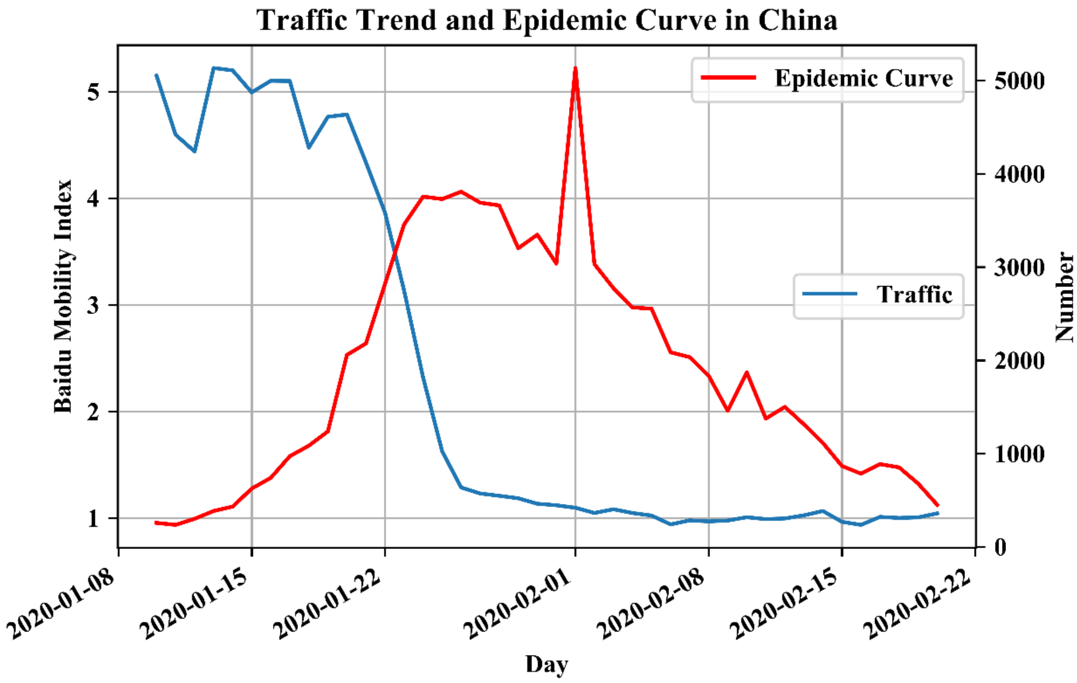


Figure 2: Baidu Mobility Index and epidemic curve during COVID-19 outbreak in China

The Baidu Mobility Index averaged cross 106 cities with weights of the total number of cases as of March 9 is plotted from January 10 to February 20, together with and the Chinese epidemic curve. With the decline in the Baidu Mobility Index, the number of new-onset cases also declines accordingly.

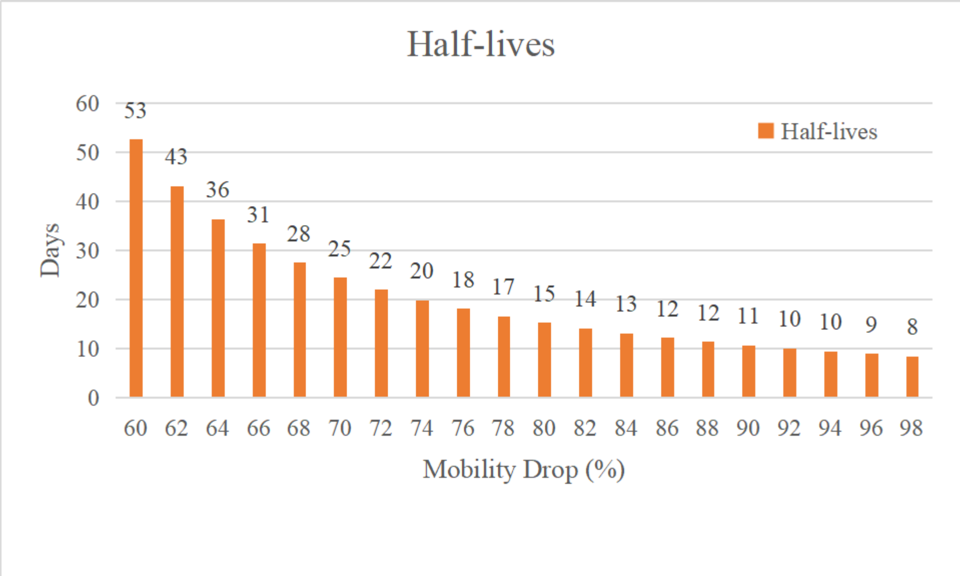


Figure 3: Half-lives vs. levels of mobility drops (%)

This figure shows the half-life horizon, i.e. the time span for the new-onset case number to be one-half of the original, vs. different levels of mobility drops, calculated with the model (1) or (2) in Table 1. We use BMI of 5 as the normal mobility level. The half-life horizon decays rapidly with mobility drops.

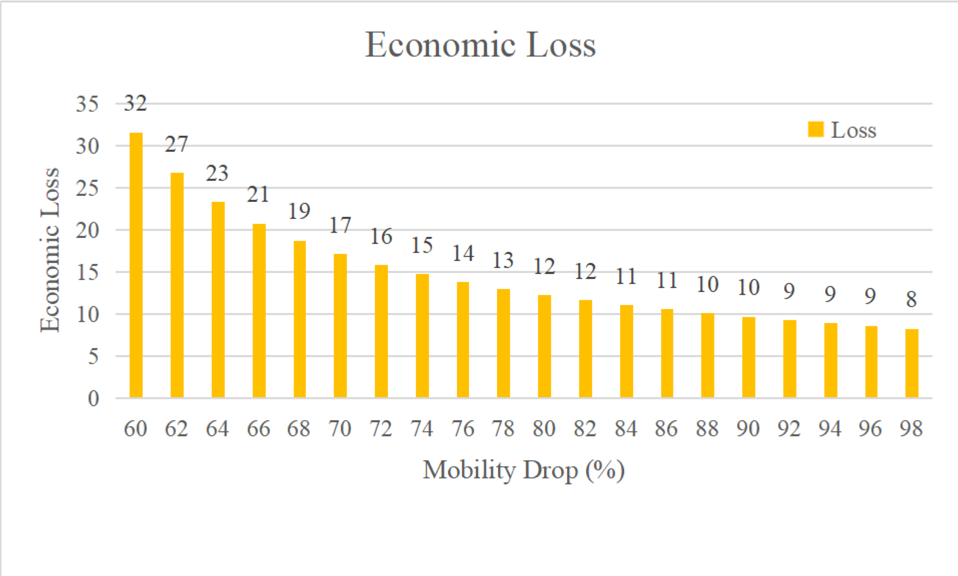


Figure 4: Economic loss vs. levels of mobility drops (%)

This figure shows the relationship between economic loss and different levels of mobility drops. The economic loss of 1% mobility drop is assumed to be 1 for simplicity. We use BMI of 5 as the normal mobility level. The economic loss falls with mobility drops.

Table 1: Baidu Mobility Index and the growth rate of new onset-case number: A Fama-Macbeth Regression

This table reports the Fama-Macbeth two-step regression coefficients for the growth rate of new-onset-case number in 7 days (a serial interval):

$$g(i,t+7) = const + b_t * BMI(i,t) + controls + u$$

where $g(i,t+7)$ is the growth rate of new-onset cases in 7 days (a serial interval) for the i^{th} city, $BMI(i,t)$ is the Baidu Mobility Index for the i^{th} city observed at day t. Temperature, relative humidity from January 24 to February 24, 2020 and the GDP per capita and population density of 2018 are used in this regression. **(1)** and **(3)** report the regression coefficients and t-statistics with and without controls, respectively, with **(2)** and **(4)** reporting the t-statistics adjusted by Newey-West standard errors with 7 lags accordingly. T-statistics are in the italic format with *, ** and *** representing significance at the 10%, 5% and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**
BMI Index	0.183	0.183	0.178	0.178
t-statistic	*6.01****	*5.81****	*4.16****	*3.22****
Temperature			-0.00449	-0.00449
t-statistics			*-0.52*	*-0.40*
Relative Humidity			*-0.0434*	*-0.0434*
t-statistics			*-1.56*	*-1.14*
GDP per Capita			-0.0100	-0.0100
t-statistics			*-1.01*	*-0.59*
Population Density			-0.0288	-0.0288
t-statistics			*1.09*	*0.69*
const	-0.454	-0.454	-0.0499	-0.0499
t-statistics	*-8.03****	*-6.49****	*-0.19*	*-0.16*
R^2	3%	3%	16%	16%

Methods

1. Data

We obtain the Baidu Mobility Index from the Baidu Migration Map (https://qianxi.baidu.com/) from January 10 to February 20, 2020 for 106 cities in China. The Baidu Mobility Index is measured by the number of outside residents in a city divided by the resident population of this city in each day, then multiply a constant to form an index. Note that the BMI can be considered as a direct measure of the degree of the traveling population within a city.

We also construct epidemic curves for all 106 Chinese cities used in this study from their first-case dates to February 24. The epidemic curves are used to estimate the growth rate, g, of new-onset case number in 7 days (a serial interval):

$$g(t+7) = \frac{N(t+7) - N(t)}{N(t)} \quad (1)$$

where $N(t)$ denotes the new symptom-onset cases at day t for a certain city.[7]

Control variables such as temperature and relative humidity are obtained from 699 meteorological stations in China from http://data.cma.cn/. If a city does not have a meteorological station inside it, we then the closest station as a proxy. Population density and GDP per capita of 2018 are obtained from https://data.cnki.net for 106 cities.

Table SI 1 provides summary statistics of the variables used in this paper.

[Figure SI 1 about here.]

2. Fama-Macbeth Regression

As shown in Figure 1, trends exist in both mobility index and epidemic curves in nearly all Chinese cities, therefore, direct time-series regressions cannot be employed. We, therefore, borrow the Fama-Macbeth[1] methodology from the finance literature to perform our estimation. Particularly, on each day t, we perform a cross-sectional regression for different cities of the following:

$$g(i, t+7) = const + b_t * BMI(i, t) + controls + u \quad (2)$$

[7] Note that if N(t) is 0 and N (t+7) is a positive number, we set N as 1 in order to make the division valid.

where $g(i, t+7)$ is the growth rate of new onset cases from t to t+7 for the i^{th} city, $BMI(i, t)$ is the Baidu Mobility Index for the i^{th} city observed at day t. We also add temperature, relative humidity on each day t and GDP per capita and population intensity for each city as control variables in the cross-sectional regressions from January 24 to February 24. b_t is the regression coefficient of BMI at day t. After getting b_ts for all days in the sample, we use the average of b_ts to estimate the coefficient of BMI. Since serial dependence exists for $g(t)$ up to 7 lags, we use Newey-West adjustment with 7 lags when calculating the t-statistics of the average. The regressions are performed with the econometrics software *Stata*.

3. Robustness Checks

As mentioned earlier, there was a very steep spike on February 1 on the epidemic curve, and therefore, as a robustness check, we remove the observations on February 1 and re-do the Fama-Macbeth regression. As Table SI 2 shows, the robustness check results are very close to our original results in Table 1.

[Table SI 2 about here.]

Table SI 1: Data Summary

This table summarizes variables used in this paper for 106 cities from January 24 to February 24, 2020.

	Mean	**Std**	**Min**	**Max**
Growth Rate of New-onset-case number in 7 Days	-0.0444	1.228	-0.989	19.000
Baidu Mobility Index	2.212	1.057	0.569	6.339
Temperature (Celsius)	5.538	6.660	-23.000	22.700
Relative Humidity (%)	75.617	14.754	22.000	100.0
GDP per Capital (RMB 10k)	7.109	3.872	1.387	18.594
Population Density (k/km^2)	0.791	1.025	0.00657	6.671

Table SI 2: Baidu Mobility Index and the growth rate of new-onset cases: A Fama-Macbeth Regression without the observations on February 1

This table reports the Fama-Macbeth two-step regression coefficients for the growth rate of new-onset-case number in a serial interval, but without observations on February 1.

$$g(i, t+7) = const + b_t * BMI(i,t) + controls + u$$

where $g(i, t+7)$ is the growth rate of new-onset-case number in 7 days for the i^{th} city, $BMI(i,t)$ is the Baidu Mobility Index for the i^{th} city observed at day t. Temperature, relative humidity from January 24 to February 24 and the GDP per capita and the population density of 2018 are used in this regression. **(1)** and **(3)** report the regression coefficients and t-statistics with and without controls, respectively with **(2)** and **(4)** reporting the t-statistics adjusted by Newey-West standard errors with 7 lags, accordingly. T-statistics are in the italic format with *, ** and *** representing significance at the 10%, 5% and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**
Baidu Mobility Index	0.183	0.183	0.177	0.177
t-statistic	*5.80****	*5.65****	*4.02****	*3.19****
Temperature			-0.00425	-0.00425
t-statistics			*-0.48*	*-0.38*
Relative Humidity			*-0.00453*	*-0.00453*
t-statistics			*-1.58*	*-1.12*
GDP per Capita			-0.0106	-0.0106
t-statistics			*-1.03*	*-0.61*
Population Density			-0.0298	-0.0298
t-statistics			*-1.09*	*-0.70*
const	-0.445	-0.445	-0.0257	-0.0257
t-statistics	*-7.72****	*-6.59****	*-0.09*	*-0.08*
R^2	3%	3%	17%	17%