Can Early Diagnostic Confirmation Save More Lives during the COVID-19 Pandemic? Evidence from China

Simiao Chen, Zhangfeng Jin, Till Bärnighausen, David E. Bloom *

Abstract: This paper investigates the impact of early diagnostic confirmation on the COVID-19 pandemic in a developing country. Utilizing a dataset of the first laboratory-confirmed cases across Chinese cities, we show that reducing the time to publicly confirm the first case in a city by one year leads to reductions of 9.4% in COVID-19 prevalence and 12.7% in mortality over the subsequent six months. The impact was more pronounced in cities farther from the COVID-19 epicenter, with lower migration exposure, more responsive public health systems, and higher health system capacity utilization. Enhanced social distancing and a less overstressed health system likely drive these effects. Our findings advocate for allocating resources to improve diagnostic technologies, strengthening public health emergency response systems to test for, diagnose, and announce cases of infection, and acting swiftly when facing a potential outbreak.

Keywords: Diagnostic Time; Information Disclosure; Social Distancing; COVID-19; China

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* Chen: Heidelberg University, Chinese Academy of Medical Sciences, and Peking Union Medical College; email: simiao.chen@uni-heidelberg.de. Jin (corresponding author): Zhejiang University of Technology, Liuhe Road No. 288, Hangzhou, 310000, China; email: zhangfeng_jin@zjut.edu.cn. Bärnighausen: Heidelberg University; email: till.baernighausen@uni-heidelberg.de. Bloom: Harvard T.H. Chan School of Public Health; email: dbloom@hsph.harvard.edu. We appreciate valuable comments from the participants at the Impact Evaluation Conference for KDI School's 25th Anniversary. A previous version of this manuscript was titled "Act Early to Prevent Infections and Save Lives: Causal Impact of Diagnostic Time on the COVID-19 Pandemic." We are grateful to the National Bureau of Statistics and Tsinghua China Data Center, China Data Lab, the Data-center of China Public Health Science of the Chinese Center for Disease Control and Prevention, and Baidu Migration for providing access to Population Census Data (2015), China COVID-19 Daily Cases with Basemap, past infectious diseases data, daily migration data, and other datasets. The opinions expressed in this paper are those of the authors. All errors are our own. The authors are grateful to Maddalena Ferranna for helpful comments.

1 Introduction

Investing in diagnostic and surveillance systems to provide early warnings of new coronaviruses entering human populations is crucial but often overlooked. The COVID-19 pandemic, which has caused significant global fatalities, highlights the need to examine this issue closely. Many countries responded with restrictive measures such as city-wide lockdowns and travel bans, which may have helped reduce the spread and impact of COVID-19 (Aum, Lee, and Shin 2020; Briscese et al. 2020; Chen, Yang, et al. 2020; Chen, Zhang, et al. 2020; Chen, Chen, et al. 2020a; 2021). However, these measures also imposed substantial social and economic costs (Adda 2016; Alvarez, Argente, and Lippi 2020; Acemoglu et al. 2020; Do et al. 2020). In contrast, early public health interventions, such as efficient diagnosis and isolation, could have significantly reduced disease transmission and potentially lessened the need for more disruptive measures. But to what extent early diagnostic confirmation could have mitigated the pandemic's consequences remains unclear.

In this paper, we examine the extent and how diagnostic time—the period between a patient's first doctor visit for COVID-19 symptoms and the public confirmation of the first case—affected the COVID-19 pandemic across 275 Chinese cities (**Figure 1**).

For well-understood diseases like tuberculosis or HIV, the time to diagnose a case is typically independent of when the patient first seeks care. However, for emerging diseases with limited knowledge and diagnostic technology, diagnosing the first case in any location can be complicated and lengthy, requiring strict criteria. For example, early in the COVID-19 pandemic, confirming the first local cases involved showing a high degree of genetic similarity between a patient's viral specimen and known COVID-19 samples. Moreover, in China, provincial-level and city-level health authorities could not release information about first cases until the central or provincial health authorities verified the results. This top-down approach helped reduce the risk of misdiagnosis at the start of local outbreaks but also delayed the confirmation of initial cases.

The time to confirm the first COVID-19 case became significantly shorter after January 18, 2020, when the central health authority issued new official guidance (Version 2) for diagnosing the first case in each province outside of Hubei, where COVID-19 was first reported (**Figure 1**). This new guidance allowed for the use of real-time fluorescent polymerase chain reaction (RT-PCR) testing, which detects specific genetic material of the virus, as an alternative to the previous method that required confirming the viral gene sequence was highly similar to known coronaviruses. The introduction of RT-PCR testing made it much quicker for city-level

health authorities to confirm their first cases, especially after the first in a province was confirmed. However, this quicker diagnostic method involves a trade-off, as faster results can sometimes mean reduced diagnostic accuracy.

To estimate the impact of diagnostic time, we use an instrumental variable (IV) approach based on the quasi-random date when the first diagnosed patient in a locality visited a doctor. This randomness comes from the uncertainties in the incubation period and the timing of seeking medical care. Specifically, we construct an IV based using the time interval between January 19, 2020, when the updated official guidance (Version 2) on diagnostic confirmation was issued, and the date the first patient in a locality saw a doctor. We call this the *time interval from the revised policy to the first doctor visit* (**Figure 1**).

To ensure the validity of the IV, it is essential that, given observable characteristics such as the rough timing of infection, the timing of the first doctor's visit by the first diagnosed patient in a locality is quasi-random and independent of the outcomes of interest. This assumption seems reasonable because the incubation period can last up to 14 days after infection (World Health Organization 2020b), and individuals vary significantly in when they seek care upon developing symptoms. We also provide empirical evidence to support this IV assumption.

The main findings of our study are as follows. Firstly, shortening the time to confirm the first COVID-19 case by one day resulted in a 9.4% reduction in COVID-19 prevalence and a 12.7% reduction in mortality over the subsequent six months. Secondly, the impact was more pronounced in cities farther from the COVID-19 epicenter, those with less prior migration exposure, more responsive public health systems, and higher health system capacity utilization. Thirdly, enhanced social distancing and less burdened health systems likely contributed to these effects. Finally, these impacts were sustained over time. These findings highlight the critical role of prompt diagnostic confirmation in mitigating the spread and impact of COVID-19.

This paper addresses a critical research gap by examining the impact of diagnostic time on the spread and impact of epidemics. While several studies have used mathematical modeling, such as susceptible-exposed-infected-recovered (SEIR) models (Chowell et al. 2015; Nouvellet et al. 2015; Rong et al. 2020), and nonparametric statistical methods like those proposed by Harris (2020) to estimate reporting delays of confirmed COVID-19 cases in New York, they primarily focus on early diagnosis of all cases rather than the first case. Importantly, these studies do not explore how early diagnosis specifically affects epidemic mitigation in the context of government and society responsiveness.

Furthermore, this paper contributes to the expanding literature that empirically

investigates various factors influencing COVID-19 spread and impact, including climate and nonpharmaceutical interventions (Fang, Wang, and Yang 2020; Chen, Prettner, et al. 2021; Qiu, Chen, and Shi 2020; Pan et al. 2020). Lastly, it adds to the body of research examining how information disclosure impacts public health outcomes (Jin and Leslie 2003; Ho, Ashwood, and Handan-Nader 2019; Jin and Leslie 2019).

2 Diagnostic Time and the COVID-19 Pandemic in China

2.1 The COVID-19 Pandemic in China

COVID-19 was first reported in Wuhan, the capital city of Hubei Province, China, in December 2019 (Wang et al. 2020). China's response to COVID-19 was much improved compared to its handling of the SARS outbreak, thanks to the lessons learned during that earlier crisis (Wilder-Smith, Chiew, and Lee 2020). In early January 2020, Chinese researchers obtained and released the genetic sequence of the virus causing COVID-19 (Wang et al. 2020). However, early diagnostic confirmation was initially cautious due to limited knowledge about the virus.

The Diagnosis and Treatment Protocol for Novel Coronavirus Pneumonia (Trial Version) was first released on January 16, 2020.[1] Initially, the disease was referred to internationally as "novel coronavirus (2019-nCoV)" in January 2020 and was officially named "coronavirus disease 2019 (COVID-19)" by the World Health Organization (WHO) on February 11, 2020 (World Health Organization 2020a). China later adopted this name in line with the WHO recommendations.

Early guidance required a high degree of genetic sequence homology between a patient's viral specimen and previously identified COVID-19 samples to confirm an infected case. This stringent criterion complicated and slowed down the diagnostic process. On January 18, the criteria were updated to allow a positive result from a fluorescent RT-PCR test to confirm an infected case, streamlining the process.[2]

For the first case confirmed at the provincial level outside Hubei, the central health authority still needed to compare genetic sequence after a positive RT-PCR result from the local health authorities. However, subsequent confirmations within the same province did not require this additional verification. Thus, after January 18, the introduction of the fluorescent RT-PCR

[1] The Health Commission of Hubei Province released this information at the official website: http://wjw.hubei.gov.cn/bmdt/ztzl/fkxxgzbdgrfyyq/jkkp/202003/t20200307_2174481.shtml.

[2] The official guidance on diagnostic confirmation was updated another five times on January 22, January 27, February 4, February 18, and most recently (Version 7) on March 3, 2020. Details of the Diagnosis and Treatment Protocol for Novel Coronavirus Pneumonia (Trial Version 7) can be found at https://www.chinalawtranslate.com/wp-content/uploads/2020/03/Who-translation.pdf.

kit significantly shortened the time needed for diagnostic confirmation in cities where COVID-19 cases had already been confirmed.

2.2 Why does Diagnostic Time Matter?

Diagnostic time—the interval between the onset of symptoms and the public announcement of a city's first COVID-19 case—serves as a crucial indicator of a government's awareness and transparency. Reducing this time enables earlier responses to outbreaks, potentially shortening lockdown periods and avoiding the drawbacks of prolonged nationwide lockdowns and travel restrictions. Firstly, early outbreak response can significantly reduce infections and deaths. Studies indicate that timely intervention is more effective in controlling disease spread (Berger, Herkenhoff, and Mongey 2020; Chudik, Pesaran, and Rebucci 2020; Eichenbaum, Rebelo, and Trabandt 2020; Chen, Chen, et al. 2020b). Secondly, rapid diagnosis can alleviate the negative social effects of long-term lockdowns, such as massive protests and social unrest (Dyer 2020). Thirdly, efficient diagnostics help minimize the economic toll of extended lockdowns by enabling quicker intervention and resolution of the epidemic (Aum, Lee, and Shin 2020; Acemoglu et al. 2020; Alvarez, Argente, and Lippi 2020).

Shortening diagnostic times helps limit infections and deaths through several key channels: Firstly, quick diagnosis allows for the prompt isolation of infected individuals, reducing community transmission (Omar et al. 2020; Chen, Zhang, et al. 2020). Secondly, early announcements inform the public, prompting preventive measures like mask-wearing, frequent hand washing, and social distancing (Chan and Yuen 2020; Cheng et al. 2020; Feng et al. 2020). Third, local authorities can swiftly implement outbreak-control measures such as contact tracing, disease screening, and mask mandates (Anderson et al. 2020; Chen, Yang, et al. 2020; Kraemer et al. 2020). Fourth, rapid diagnostics help prevent overburdening healthcare systems by reducing infections and allowing for the expansion of healthcare capacities, ensuring adequate resources like ICU beds and ventilators (Armocida et al. 2020; Cavallo, Donoho, and Forman 2020; Woolley 2020; Chen, Zhang, et al. 2020; Ji et al. 2020). Finally, timely information allows various sectors, including academic institutions, companies, and media, to take early and appropriate actions (Ranney, Griffeth, and Jha 2020; Simonov et al. 2020; Bavel et al. 2020).[3]

[3] For example, academic institutions and universities can initiate scientific research to model the epidemic evolution and evaluate economic and social impact; companies can prepare by shifting production to items relevant to outbreak control, such as protective masks, surgical gloves, and nucleic acid testing kits; and media outlets can start assimilating knowledge of the new disease and interviewing experts to educate the population.

While the exact extent to which early diagnostic confirmation could have mitigated the pandemic's consequences is still unclear, the potential benefits highlight the importance of seeking direct empirical evidence on this matter.

3 Data Sources and Main Variables

To construct the health outcome variable, we rely on two data sources. The first source is the China Data Lab (Lab 2020), which provides the cumulative number of confirmed COVID-19 cases, including both infections and deaths, for each city from January 15, 2020, to August 2, 2020. The second source is the China City Statistical Yearbook 2019 (National Bureau of Statistics of China 2020), which offers the total number of registered residents in each city as of the end of 2018. We include all cities that appear in both datasets and have at least one laboratory-confirmed infected COVID-19 case, excluding the city of Wuhan. The final sample consists of 275 cities across 31 provinces and municipalities. We define COVID-19 prevalence as the ratio of cumulative laboratory-confirmed infected cases to the total registered population (in millions) in each city by August 2, 2020, and define COVID-19 mortality as the ratio of cumulative confirmed deaths to the total registered population (in 100 millions) in each city by August 2, 2020.

For the diagnostic time variable, we construct a novel dataset detailing the profile of the first laboratory-confirmed cases across all cities in mainland China. This dataset includes general information on the first infected individuals, such as their age, gender, travel history (including the timing of their return home from the COVID-19 epicenter or other cities with confirmed cases), timing of symptom onset, timing of their first visit to a doctor, timing of diagnostic confirmation, and timing of recovery or death. To measure diagnostic time, we use the interval between the date of first doctor's visit and the date of diagnostic confirmation.

We construct other relevant city-level variables as follows.

1. Travel Time to Wuhan: We construct a dataset containing the longitude and latitude of each city and calculate the travel time of the shortest route in hours by car between each city and the city of Wuhan using the Open Source Routing Machine based on OpenStreetMap data.

2. Economic and Health Data: We gather city-level data on gross regional product (GRP) per capita, industry structures (including percentage of secondary and tertiary industries in GRP), the number of hospital beds per thousand people, and number of public health staff per thousand people from the China City Statistical Yearbook 2019 (National Bureau of Statistics of China 2020).

3. Provincial Health Data: We collect provincial-level data on the total number of patients and discharged patients from hospitals from January 2020 to April 2020, provided by the National Health Commission of the People's Republic of China.

4. Public Health Alerts: We gather official news on the launch date for the Level-1 Public Health Incident Alert, the highest level of China's public health alert system, for each province or municipality. We construct a measure of the time interval between the date when the first infected case was publicly confirmed at the provincial level and the launch date of the Level-1 Public Health Incident Alert, referred to as the "*time interval (first case to public health alert)*" (**Figure 1**).

5. Influenza Data: We collect city-level data on influenza cases in 2018 from the Data-center of China Public Health Science of the Chinese Center for Disease Control and Prevention.

6. Migration Data: We use two sources for migration data:

The first is the China Population Census Survey 2015 (National Bureau of Statistics of China 2018). We use the percentage of migrants in the population prior to COVID-19 emergence to measure migration intensity across cities. Additionally, we use the percentage of migrants from the COVID-19 epicenter prior to the emergence of COVID-19 to assess the risk of importing the disease through established migration networks.

The second data source is the Baidu Migration Data. This travel map offered by China's largest search engine, Baidu. offers daily travel intensity (*migration index*) indicators. The Baidu Migration Data provide three travel intensity indicators: travel intensity within cities (*within-city migration index*), travel intensity to other cities (*out-migration index*), and travel intensity from other cities (*in-migration index*). **Table 1** reports summary statistics for the main variables. **Appendix A (Figures A1–A9)** provides further descriptive details for these variables.

4 Model Specification and Identification Strategy

To examine the impact of diagnostic time on the COVID-19 pandemic, we use the following two stage least squares (2SLS) model:

$$D_c = \beta_D^Z \cdot Z_c + \beta_D^K \mathrm{K_c} + \varepsilon_c \quad (1)$$

$$Y_c = \beta_Y^D \cdot D_c + \beta_Y^K \mathrm{K_c} + \eta_c \quad (2)$$

where c is the city index, Y_c is the logarithm of the prevalence or mortality of COVID-19 in city c, D_c is the time taken to confirm the first case publicly in city c, Z_c is the instrument variable (IV), defined as the time interval between January 19, 2020 and the date when the first

diagnosed patient in a locality first visited a doctor in city c, and $\mathrm{K_c}$ is a vector of city characteristics. The city characteristics include: travel time from city c to the COVID-19 epicenter, percentage of migrants from the COVID-19 epicenter in the population prior to COVID-19's emergence in city c, GRP per capita, composition of industry structures, number of hospital beds per thousand people, number of public health staff per thousand people, capacity utilization of health systems, time interval (first case to public health alert) at the provincial level, and provincial-level fixed effects. ε_c and η_c are the error terms. The parameter of interest is β_Y^D, which captures the impact of diagnostic time on COVID-19 prevalence or mortality locally.

As explained previously, diagnostic time is associated with several factors that affect the health outcomes of interest. For example, the risk of importing infected cases from the COVID-19 epicenter is positively associated with local COVID-19 prevalence or mortality. If the risk is also positively associated with diagnostic time, omitting this variable will bias the OLS estimate upward. Additionally, local authorities may pursue different strategies to prevent disease transmission. For instance, some local authorities may be less efficient in information disclosure but more efficient in adopting rigorous measures, such as area quarantines, to control the disease. Omitting the variable could bias the OLS estimate downward.

To address these potential endogeneity problems, we construct an IV based on the time interval between the revised policy and the first doctor's visit. The rationale is that cities where the first diagnosed patient's initial visit to a doctor occurred earlier (i.e., with a smaller value of the IV) typically spent more days confirming the first case to the public on average. Furthermore, conditional on observable characteristics, the timing of the first infected person's initial doctor visit depends on quasi-random factors such as the incubation period, which can last up to 14 days, and the timing of seeking care, which varies across individuals according to their time of symptom onset. Our IV strategy identifies the local average treatment effect for cities where the first infected person was publicly confirmed in less time because their first doctor visit occurred at a later date, when more efficient diagnostic technologies and process were available.

The validity of the IV depends on two important assumptions. The first is relevance assumption, that is, the time interval between revised policy and the first doctor's visit is negatively associated with diagnostic time. This means that a shorter time interval should correlate with longer diagnostic times. This assumption can be empirically tests.

The second is exclusion restriction assumption, that is, conditional on observable

characteristics, the quasi-random date when the first diagnosed patient in a locality first visited a doctor affects COVID-19 prevalence or mortality only through the diagnostic time variable. This implies that other than through its impact on diagnostic time, the initial doctor's visit date should not have a direct effect on the health outcomes. This assumption is more challenging to test empirically but is crucial for the IV's validity.

In addition to controlling for various city characteristics as described above, we provide further empirical validation of the IV exclusion restriction assumption through the following methods:

1. Controlling for the rough timing of infection: We include variables that capture the general timeline of when the infection first occurred in each city to ensure that our results are not driven by the timing of the initial infections.

2. Regressing measures of past disease severity and spread on the IV with the included controls: We test whether our IV is correlated with past measures of disease severity and spread, controlling for the other variables in our model. If the IV is uncorrelated with these past measures, it supports the exclusion restriction assumption.

3. Focusing on cities with similar dates of the first case's first visit to a doctor: By limiting our analysis to cities where the first diagnosed patient's initial doctor visit occurred around the same time, we reduce the potential bias from differences in infection timelines.

4. Introducing a new IV: We introduce an additional IV and compare the parameter of interest using different IVs. This allows us test the validity of our instruments through overidentification test, providing further evidence for the validity of the IV.

5 Empirical Results

This section answers three questions. First, to what extent does diagnostic time affect COVID-19 prevalence and mortality? Second, are the impacts of diagnostic time heterogeneous across groups? Third, what is the likely underlying mechanism through which the diagnostic time affects COVID-19 prevalence and mortality?

5.1 Impact of Diagnostic Time on the COVID-19 Pandemic

We begin by reporting the OLS estimates for the associations between diagnostic time and the prevalence of COVID-19 infections, as well as between diagnostic time and COVID-19 mortality (**Table 2**). The unadjusted estimates (i.e., without controlling for other variables) reported in Column 1 of **Table 2** show that, on average, a 1-day reduction in the time to publicly confirm the first infected case is associated with a 15% decrease in the prevalence of COVID-

19 infections and a 22% decrease in COVID-19 mortality.

Columns 2–7 in **Table 2** present the further adjusted OLS estimates, incorporating additional covariates. In the preferred multivariable regression, after controlling for provincial-level fixed effects (column 7), we find that the association between diagnostic time and COVID-19 prevalence or mortality decreases to 0.00 or 0.03, respectively. Thus, the OLS estimates show an insignificant association between diagnostic time and COVID-19 infections or deaths. **Appendix B (Tables A1-A2)** provides more details on the coefficients of other covariates.

As discussed previously, the OLS estimate may be biased due to endogeneity problems. The IV estimate reported in Column 8 of **Table 2** reveals that, on average, a 1-day reduction in the time to publicly confirm the first infected case leads to about a 9.4% decrease in the local prevalence of COVID-19 infections and a 12.7% decrease in local COVID-19 mortality. This suggests that the OLS estimates are seriously underestimated. One explanation for this underestimation is that local authorities delaying the confirmation of COVID-19 may subsequently implement more rigorous actions, such as longer lockdown durations, to contain disease transmission. Omitting this variable biases the OLS estimates downward.

The first-stage results reported in Column 9 of **Table 2** show that a one-standard-deviation (4.5 days) increase in the time interval (revised policy to first doctor visit) leads to about 2 fewer days to confirm the first case locally. The F-stat for the weak identification test is 237, suggesting that our IV does not suffer from weak identification problems.[4] Additionally, the results of the Durbin–Wu–Hausman test reject the null hypothesis that the OLS estimators are consistent and efficient (Nakamura and Nakamura 1981; Baum, Schaffer, and Stillman 2007) (see more details in **Table 2**). Collectively, this evidence supports the validity of our IV approach.

To address concerns that the IV exclusion restriction assumption may be violated, we further control for the rough timing of infection (i.e., the relative timing of returning home from the COVID-19 epicenter or other cities with confirmed infected cases). Controlling for the rough timing of being infected does not alter our main findings. Moreover, the coefficient of the timing of infection variable is close to zero and not statistically significant at the conventional level (Column 1 of **Tables A3** and **A4**).

We also examine the impact of the IV on past disease severity and spread by regressing measures of past disease severity and spread on the IV with the included controls. Using city-

[4] We find robust results when using a Montiel-Olea-Pflueger effective F statistic that does no rely on an assumption of homoskedasticity (Olea and Pflueger 2013).

level influenza prevalence in 2018 to proxy for the past disease severity and spread, our empirical results show no significant impact of the IV on the influenza prevalence (Column 1 of **Table A5**). In contrast, we find a significant impact of the IV on COVID-19 prevalence (Column 2 of **Table A5**).

To further validate the IV exclusion restriction assumption, we focus on cities with similar dates for the first case's initial doctor visit and apply different cutoffs, ranging from 4 to 7 days around the date when the local government adopts the updated official guidance (Version 2) on diagnostic confirmation of the first case outside Hubei province. Using alternative cutoffs does not change our main findings regarding COVID-19 prevalence (Columns 2-5 of **Table A3**).[5]

Finally, to formally test instrument validity, we propose a new IV based on whether the first case's initial doctor visit occurred after the introduction of more efficient diagnostic technologies and process. Using the new IV, the coefficient of interest regarding COVID-19 prevalence is 0.06. The first-stage result also confirms that cities where the first case's initial doctor visit occurred after January 18, 2020, spent fewer days confirming the first infected case. Additionally, we use both instruments to test IV validity, finding a coefficient of interest of 0.08. The bottom row of **Table A6** reports results of the overidentification test, which fails to reject the null hypothesis that the instruments are valid. Similar results are found when focusing on cities with similar dates for the first case's initial doctor visit using different cutoffs.

5.2 Heterogeneous Effects

We further explore whether the impact of diagnostic time varies across cities using the same IV approach.

Firstly, we compare cities closer to the COVID-19 epicenter with those farther away. A 1-day reduction in the time to publicly confirm the first case results in about a 17% decrease in local COVID-19 prevalence and a 26% decrease in local COVID-19 mortality in cities farther from the COVID-19 epicenter (above the median travel time distribution). In comparison, the same reduction leads to smaller decreases (6% in prevalence and 7% in mortality) in cities closer to the epicenter (Columns 1–2 of **Table 3**).

Secondly, we examine cities with varying levels of migration prior to COVID-19. In cities with less migration (below the median migration intensity), a 1-day reduction in confirmation time results in about a 19% decrease in prevalence and a 25% decrease in mortality. However,

[5] The insignificant result for the COVID-19 mortality suggests a bias-variance trade-off when selecting cut-offs (Columns 2-5 of **Table A4**). In particular, many cities with COVID-19 infections did not experience any COVID-19 deaths during our sample period, which may make the problem worse.

in cities with more migration, the reduction only leads to 5% decreases in both prevalence and mortality (Columns 3–4 of **Table 3**).

Thirdly, we analyze cities based on the responsiveness of their public health systems, measured by the time interval from the first case to a public health alert. In cities with more responsive systems (below the median response time), a 1-day reduction in confirmation time leads to about 26% lower prevalence and 25% lower mortality. In cities with less responsive systems, the decreases are only 3% and 6%, respectively (Columns 5–6 of **Table 3**).

Finally, we compare cities based on the capacity utilization of their health systems, using the ratio of patients from January 2020 to April 2020 to the same period in 2019. In cities with higher-capacity utilization (above the median), a 1-day reduction in confirmation time results in about a 13% decrease prevalence and a 20% decrease in mortality. In cities with lower-capacity utilization, the decreases are 9% and 11%, respectively (Columns 7–8 of **Table 3**).

In summary, the impact of reducing diagnostic time is more significant in cities that are farther from the epicenter, have less migration, more responsive public health systems, and higher-capacity utilization of health systems.

5.3 Potential Mechanisms

Why does diagnostic time matter for the COVID-19 pandemic? A plausible mechanism through which shortened diagnostic time reduces COVID-19 infections and deaths is enhanced social distancing. To confirm this mechanism, we examine the impact of publicly confirming the first case on travel intensity within and between cities using a difference-in-differences framework.

We use high-frequency daily data from the Baidu Migration platform on intra-city travel intensity, travel intensity to other cities, and travel intensity from other cities between January 1, 2020, and March 15, 2020. This data is combined with the exact date of diagnostic confirmation for the first infected case in each locality. The model specification is as follows:

$$y_{ct} = \alpha' I_c + \beta' I_t + \gamma\, I_{c,t \geq t_{first\ case}} + \varepsilon_{ct} \quad (3)$$

where y_{ct} is the travel intensity indicator (within-city migration index, out-migration index, or in-migration index) in city c on day t, I_c is the vector of city fixed effects, I_t is the vector of time fixed effects, and $I_{c,t \geq t_{first\ case}}$ is a dummy variable indicating an observation after confirming the first case publicly in city c. The error term is ε_{ct}. Coefficients α and β are vectors to be estimated, and γ is the coefficient of interest. We use the estimator proposed by de Chaisemartin and D'Haultfoeuille (2020), which accounts for heterogeneous impacts across cities and over time.

Both intra-city and inter-city travel intensity decreased dramatically after confirming the first case publicly (**Figure 2**). For example, using travel intensity indicators from the same period in 2019 as a benchmark, we find that publicly confirming the first symptomatic infected case led to average reductions of 13%, 28%, and 37% in intra-city travel intensity, travel intensity to other cities, and travel intensity from other cities, respectively, three days after confirmation. We do not find similar patterns in a placebo analysis using 2019 travel intensity indicators (**Figure A10 in Appendix C**). These findings suggest that social distancing, induced by early public confirmation of the first infected case, is a likely underlying mechanism through which improved diagnostic time helps contain disease transmission.

However, social distancing alone cannot fully explain why the impact of diagnostic time is more pronounced in reducing deaths (12.7%) compared to infections (9.4%). This indicates that the impact of diagnostic time on mortality is not only due to fewer COVID-19 infections but also from other pathways.

One important and plausible pathway is the alleviation of stress on the healthcare system. A less overstressed health system can reduce treatment delays, deliver better healthcare service, ensure sufficient healthcare resources (e.g., ICU beds, ventilators), and provide better protection of vulnerable groups (e.g., the elderly and people with chronic diseases, who are more likely to die than younger and healthier populations). These factors all contribute to a higher survival probability (Armocida et al. 2020; Cavallo, Donoho, and Forman 2020; Woolley 2020; Chen, Zhang, et al. 2020; Ji et al. 2020).

Indeed, when health systems are overwhelmed, the impact of diagnostic time on COVID-19 mortality increases by 82%—from 11% in cities with lower-capacity utilization of health systems to 20% in cities with higher-capacity utilization of health systems. Meanwhile, the impact of diagnostic time on the prevalence of COVID-19 infections only increases by 44%—from 9% in cities with lower-capacity utilization of health systems to 13% in cities with higher-capacity utilization of health systems (**Table 3**). These findings suggest that the impact of diagnostic time on deaths is also due to reducing stress on health systems, allowing for better management and treatment of patients.

5.4 Persistence of the Impact of Diagnostic Time Over Time

We further explore how the impact of diagnostic time evolves over time. One possibility is that the role of diagnostic time will diminish as local authorities implement more rigorous measures (e.g., city-wide lockdowns) to contain disease transmission. To assess this, we estimate the

impact of diagnostic time on daily COVID-19 prevalence and mortality from January 25 to August 2, 2020.

Our analysis reveals that the impacts of diagnostic time on COVID-19 prevalence and mortality generally increase over time (**Figures A11–A12 in Appendix D**). This finding suggests that shortened diagnostic time complements other mobility-restriction policies in controlling disease transmission. This evidence indicates that diagnostic time leads to persistent differences in the spread of COVID-19 across cities.

5.5 Robustness Checks

We conduct several robustness checks. First, we consider the possibility that the diagnostic confirmation process for the first infected case at the provincial level differs slightly from that of the first cases in other cities of the same province and re-estimate the impact by dropping those cities that confirm the first provincial-level infected case. Second, we consider the possibility that the diagnostic confirmation process for the first infected case inside Hubei province may differ from that outside Hubei province and re-estimate the impact by dropping all cities in Hubei province. Third, we consider the possibility that the first infected case may be imported from regions other than the COVID-19 epicenter[6] and re-estimate the impact by keeping those cities that are known to have imported the first case from the COVID-19 epicenter. No obvious evidence rejects our main findings. **Tables A3–A4 in Appendix E** provide more details.

6 Discussion and Conclusion

To the best of our knowledge, this is some of the first study to investigate the impact of diagnostic time on infectious disease epidemics. The most important lesson of this study is that shortened diagnostic time is highly effective in containing disease transmission and saving lives. Another crucial finding is that implementing subsequent epidemic-control measures significantly enhances the effectiveness of diagnostic time in reducing infections and preventing deaths.

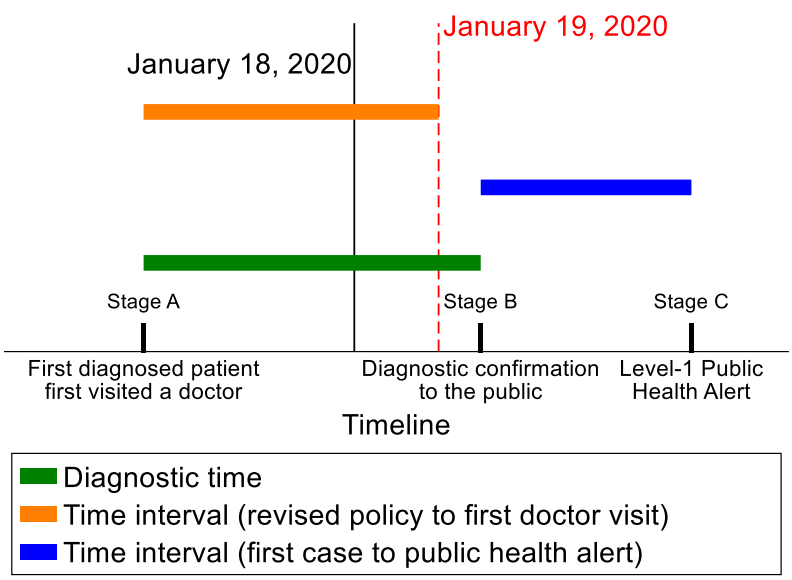
These findings shed light on the high prevalence of COVID-19 infections and high death rates in some countries (e.g., the United States), which diagnosed and publicly announced their first case in a timely manner but did not respond to the pandemic immediately. Social or cultural

[6] According to our data, about 95% of the first infected cases of other cities were imported from Wuhan city, the COVID-19 epicenter.

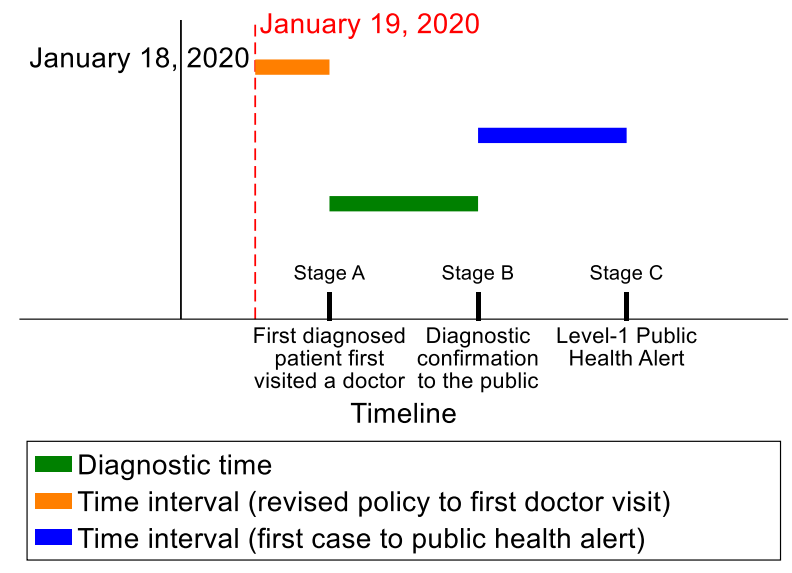
differences (e.g., collectivism versus individualism) that influence governmental and societal responses to the pandemic might mediate the effect of information disclosure in different countries. For instance, East Asian countries such as China and South Korea mandatorily isolated all COVID-19 patients, even the mildly ill, in facilities to prevent intra-family and community infections. In contrast, Western countries such as the United States and the United Kingdom recommended that mild COVID-19 patients stay at home and did not strictly enforce those recommendations (Chen, Zhang, et al. 2020; Thompson 2020; Parodi and Liu 2020).

The study has several limitations. First, the number of publicly confirmed cases may be smaller than the actual number of infected cases due to inadequate testing, asymptomatic patients, and incomplete information disclosure. This was particularly relevant at the beginning of the COVID-19 pandemic. However, this concern has become less pertinent since early February 2020 when China launched the COVID-19 policy of leaving no patient unattended or untreated, including asymptomatic patients, and started implementing universal testing campaigns to support this policy (The State Council of the People's Republic of China 2020; Pan et al. 2020; Chen, Zhang, et al. 2020). Our finding that the impact of diagnostic time persists and even increases slightly over time further reduces this concern. Second, our paper does not quantify the relative importance of different mechanisms, such as facility-based isolation of mild COVID-19 cases in *Fangcang* shelter hospitals, encouragement of mask wearing, and contact tracing, which would require structural modeling and is beyond the scope of this paper.

Overall, this study demonstrates that shortened diagnostic time is effective in reducing COVID-19 infections and saving lives. Our findings support allocating resources to improve diagnostic technologies, strengthen public health emergency response systems to test for, diagnose, and announce cases of infection, and generally act early when facing a new disease that could potentially become an outbreak.



(a)



(b)

Figure 1 Timeline of first diagnosed patient's first visit to a doctor, diagnostic confirmation to the public, and launch of the Level-1 public health alert

Note: (a) The local government adopted the updated official guidance on diagnostic confirmation of COVID-19 *after* the first diagnosed patient first visited a doctor. (b) The local government adopted the updated official guidance on diagnostic confirmation of COVID-19 *before* the first diagnosed patient first visited a doctor. The vertical solid line refers to the date when the central health authority released the updated official guidance (Version 2) on diagnostic confirmation of the first case outside of Hubei province at the national level on January 18, 2020. The vertical dashed line refers to the date when the local government adopted the updated official guidance (Version 2) on diagnostic confirmation of the first case outside of Hubei province. Diagnostic time = the time interval between the date when the first diagnosed patient first visited a doctor (**Stage A**) and the date when that first case was confirmed publicly (**Stage B**). Time interval (revised policy to first doctor visit) = the time interval between the date when a local government adopted the updated official guidance (Version 2) on diagnostic confirmation of the first case outside of Hubei province and the date when the first diagnosed patient first visited a doctor, which is also used to construct the instrumental variable adopted in the paper. Time interval (first case to public health alert) = time interval between the date when the first infected case was publicly confirmed at the provincial level (Stage B) and the launch date of the Level-1 Public Health Incident Alert (**Stage C**).

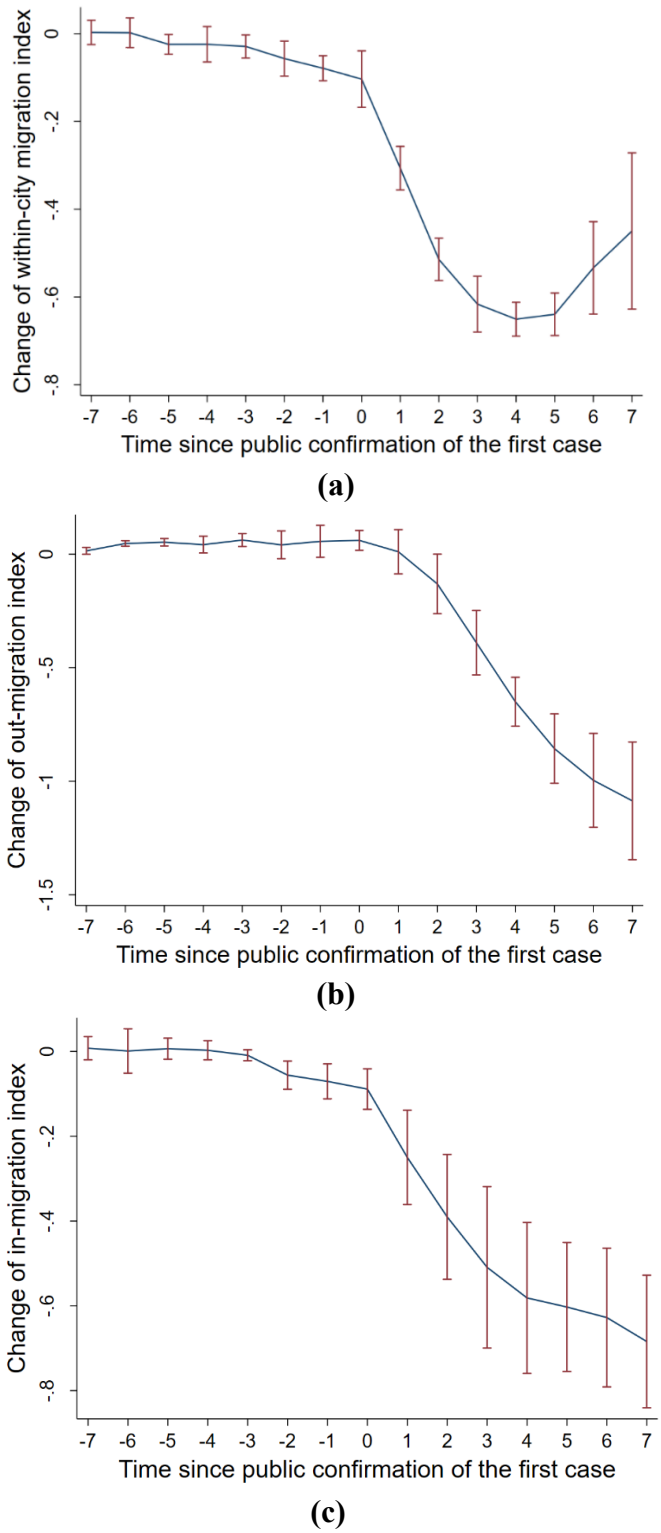


Figure 2 Impact of public confirmation of the first case on intra-city and inter-city travel intensity

Note: All daily travel intensity data come from Baidu Migration data between January 1, 2020, and March 15, 2020. (a) Impact of public confirmation of the first case on intra-city travel intensity. Within-city migration index = travel intensity within cities. (b) Impact of public confirmation of the first case on travel intensity to other cities. Out-migration index = travel intensity to other cities. These indicators are consistent across cities and across time. (c) Impact of public confirmation of the first case on travel intensity from other cities. In-migration index = travel intensity from other cities. These indicators are consistent across cities and across time.

Table 1 Summary statistics

Variables	N	Mean	Median	Std. Dev.	min	max
COVID-19 prevalence (infections per million people)	275	27.30	6.19	102.65	0.41	1255.86
COVID-19 mortality (deaths per 100 million people)	275	68.38	0.00	406.30	0.00	5315.32
Diagnostic time (days)	275	3.20	2.00	3.01	0.00	24.00
Time interval (revised policy to first doctor visit) (in days)	275	2.51	3.00	4.54	-18.00	19.00
Logarithm of travel time to the COVID-19 epicenter	275	2.32	2.40	0.63	-0.06	3.67
Percentage of migrants in the population (2015)	274	24.34	21.91	12.11	4.75	84.15
Percentage of migrants from the COVID-19 epicenter (2015)	274	0.03	0.00	0.09	0.00	0.84
Logarithm of GRP per capita (2018)	274	10.87	10.82	0.52	9.45	12.15
Percentage of secondary industry in GRP (2018)	275	42.64	43.67	9.38	15.75	63.31
Percentage of tertiary industry in GRP (2018)	275	46.49	45.34	8.41	29.48	80.98
Logarithm of hospital beds per thousand people (2018)	274	1.50	1.48	0.35	0.58	2.57
Logarithm of public health staff per thousand people (2018)	274	0.88	0.83	0.38	0.09	2.13
Utilization of health systems (total patients) (%) (2020)	275	75.22	75.55	9.39	50.11	129.98
Utilization of health systems (discharged patients) (%) (2020)	275	80.45	78.75	14.61	49.87	144.07
Time interval (first case to public health alert) (in days)	265	2.56	2.00	0.81	0.00	4.00

Note: Diagnostic time = the time interval between the date when the first diagnosed patient first visited a doctor and the date when that first case was confirmed publicly. Time interval (revised policy to first doctor visit) = the time interval between the date when a local government adopted the updated official guidance (Version 2) on diagnostic confirmation of the first case outside of Hubei province and the date when the first diagnosed patient first visited a doctor, which is also used to construct the instrumental variable adopted in the paper. Time interval (first case to public health alert) = time interval between the date when the first infected case was publicly confirmed at the provincial level and the launch date of the Level-1 Public Health Incident Alert. The prevalence and mortality of COVID-19 are as of August 2, 2020.

Table 2 Impact of diagnostic time on the COVID-19 pandemic

Variables	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) IV	(9) First Stage
				Panel A: Prevalence of COVID-19 infections					
Diagnostic time (days)	0.14	0.03	0.03	0.03	0.01	0.00	0.00	0.09	
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Time interval (revised policy to first doctor visit)									-0.51
									(0.03)
Observations	275	274	273	273	272	262	272	272	272
R-squared	0.11	0.44	0.50	0.53	0.60	0.44	0.73	0.71	0.64
F-stat	34.56	71.23	67.96	50.13	39.42	17.66	16.98	15.63	11.12
Weak identification test (Cragg-Donald Wald F statistic)	.	.	.	.	.	.	.	237.05	.
Endogeneity test of endogenous regressors (p-value)	.	.	.	.	.	.	.	0.00	.
Province dummies	No	No	No	No	No	No	Yes	Yes	Yes
				Panel B: COVID-19 mortality					
Diagnostic time (days)	0.20	0.05	0.05	0.05	0.03	0.02	0.03	0.12	
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	
Time interval (revised policy to first doctor visit)									-0.51
									(0.03)
Observations	275	274	273	273	272	262	272	272	272
R-squared	0.10	0.34	0.34	0.37	0.42	0.19	0.60	0.58	0.64
F-stat	30.42	47.27	35.19	26.07	18.96	5.40	9.07	8.91	11.12
Weak identification test (Cragg-Donald Wald F statistic)	.	.	.	.	.	.	.	237.05	.
Endogeneity test of endogenous regressors (p-value)	.	.	.	.	.	.	.	0.00	.
Province dummies	No	No	No	No	No	No	Yes	Yes	Yes

Note: This table reports the estimated impacts of diagnostic time on the COVID-19 pandemic. Panel A reports the impact of diagnostic time on prevalence of COVID-19 infections (the logarithm of COVID-19 prevalence). Panel B reports the impact of diagnostic time on COVID-19 mortality (the logarithm of COVID-19 mortality). Columns 1–7 report OLS estimates. Columns 8 and 9 report IV estimates and first-stage results, respectively. Column 1 does not control for other variables. Column 2 controls for travel time to the COVID-19 epicenter and percentage of migrants from the COVID-19 epicenter. Column 3 further controls for GRP per capita. Column 4 further controls for the composition of industrial structures. Column 5 further controls for the number of hospital beds per thousand people, the number of public health staff per thousand people, and the capacity utilization of health systems. Column 6 further controls for the time interval (first case to public health alert). Columns 7 and 8 further controls for provincial-level fixed effects. Diagnostic time = the time interval between the date when the first diagnosed patient first visited a doctor and the date when that first case was confirmed publicly. Time interval (revised policy to first doctor visit) = the time interval between the date when a local government adopted the updated official guidance (Version 2) on diagnostic confirmation of the first case outside of Hubei province and the date when the first diagnosed patient first visited a doctor, which is also used to construct the instrumental variable adopted in the paper. Standard errors are in parentheses.

Table 3 Heterogeneous impacts of diagnostic time on the COVID-19 pandemic

Variables	(1) Short distance to the COVID-19 epicenter	(2) Long distance to the COVID-19 epicenter	(3) More migration	(4) Less migration	(5) Less responsive public health system after confirmation	(6) More responsive public health system after confirmation	(7) Lower capacity utilization of health systems	(8) Higher capacity utilization of health systems
				Panel A: Prevalence of COVID-19 infections				
Diagnostic time (days)	0.06	0.16	0.05	0.17	0.03	0.23	0.09	0.12
	(0.02)	(0.06)	(0.02)	(0.06)	(0.02)	(0.06)	(0.03)	(0.05)
Observations	136	136	136	136	132	140	134	138
R-squared	0.81	0.57	0.77	0.65	0.81	0.38	0.78	0.49
F-stat	18.82	5.58	9.06	7.81	21.14	5.15	18.78	5.49
Weak identification test (Cragg-Donald Wald F statistic)	384.80	35.40	320.83	34.37	247.60	42.46	136.97	79.57
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
				Panel B: COVID-19 mortality				
Diagnostic time (days)	0.07	0.23	0.05	0.22	0.06	0.22	0.10	0.18
	(0.04)	(0.11)	(0.03)	(0.12)	(0.04)	(0.10)	(0.05)	(0.07)
Observations	136	136	136	136	132	140	134	138
R-squared	0.76	0.22	0.77	0.41	0.73	0.12	0.65	0.36
F-stat	13.82	1.59	8.96	2.98	13.66	1.54	9.65	3.13
Weak identification test (Cragg-Donald Wald F statistic)	384.80	35.40	320.83	34.37	247.60	42.46	136.97	79.57
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the heterogeneous impacts of diagnostic time on the COVID-19 pandemic. Panel A reports the heterogeneous impacts of diagnostic time on the prevalence of COVID-19 infections (the logarithm of COVID-19 prevalence) using the IV approach. Panel B reports the heterogeneous impacts of diagnostic time on COVID-19 mortality (the logarithm of COVID-19 mortality) using the IV approach. Columns 1–2 report the impacts of diagnostic time by distance from the COVID-19 epicenter. Columns 3–4 report the impacts of diagnostic time by migration intensity prior to the pandemic. Columns 5–6 report the impacts of diagnostic time by responsiveness of public health systems. Columns 7–8 report the impacts of diagnostic time by capacity utilization of health systems. Control variables include travel time to the COVID-19 epicenter, percentage of migrants from the COVID-19 epicenter, GRP per capita, composition of industrial structures, number of hospital beds per thousand people, number of public health staff per thousand people, and provincial-level fixed effects. Diagnostic time = the time interval between the date of first visiting a doctor and the date of diagnostic confirmation to the public. Standard errors are in parentheses.

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Supplementary Material: Can Early Diagnostic Confirmation Save More Lives during the Pandemic? Evidence from China

In this supplementary material, we provide additional details related to our study.

A: Further descriptive details for variables

Figures A1–A9 descriptively graph the number of total confirmed infections and deaths over time, the geographical distribution of the prevalence and mortality of COVID-19 across cities, the distribution of diagnostic time, the distribution of time interval (revised policy to first doctor visit), the geographical location of time internal (revised policy to first doctor visit) distribution, the relationship between diagnostic time and time interval (revised policy to first doctor visit), and city-level travel intensity (migration indexes) on average over time, respectively.

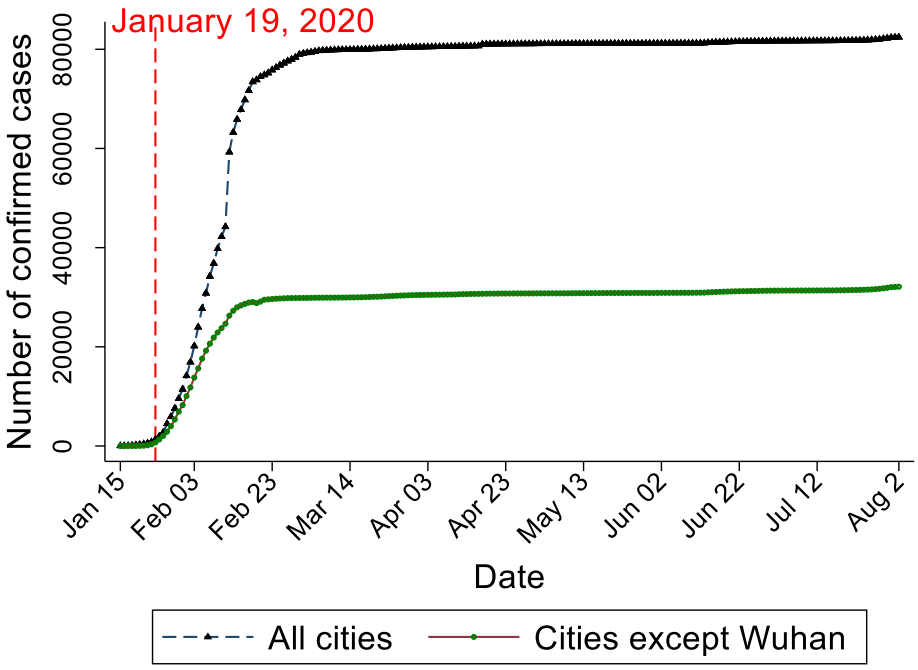


Figure A1 Total confirmed cases of COVID-19 infections over time in China
Note: All dates are in 2020

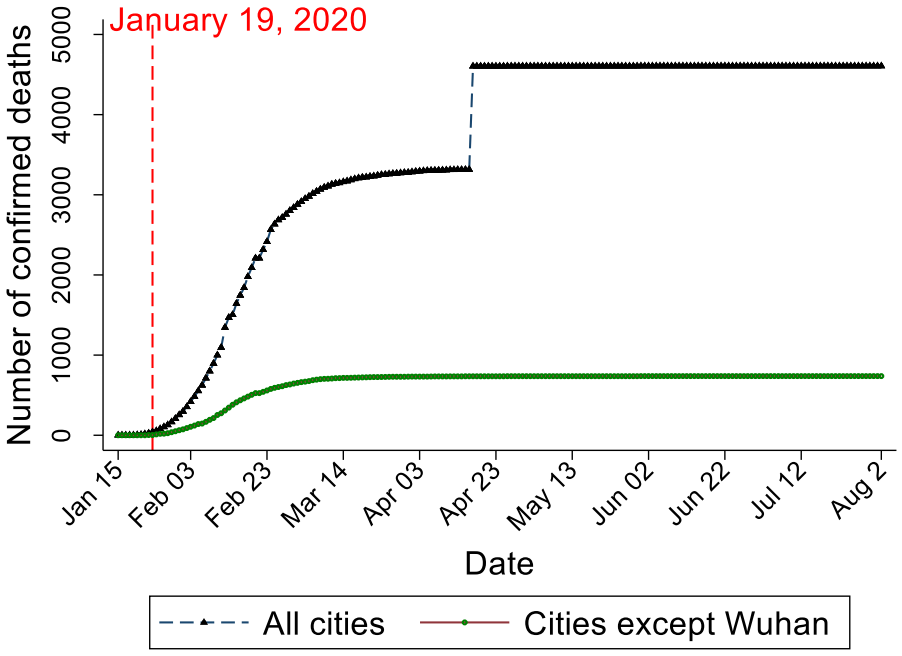


Figure A2 Total confirmed COVID-19 deaths over time in China
Note: On April 17, China added 1,290 COVID-19 deaths to Wuhan's previous tally. According to the media reports, official said the new numbers are the result of a detailed investigation, and the revised figures now include deaths that occurred at home in the beginning of the outbreak, as well as deaths that were inaccurately reported by hospitals (https://www.livescience.com/wuhan-coronavirus-death-toll-revised.html, https://edition.cnn.com/2020/04/17/asia/china-wuhan-coronavirus-death-toll-intl-hnk/index.html). All dates are in 2020.

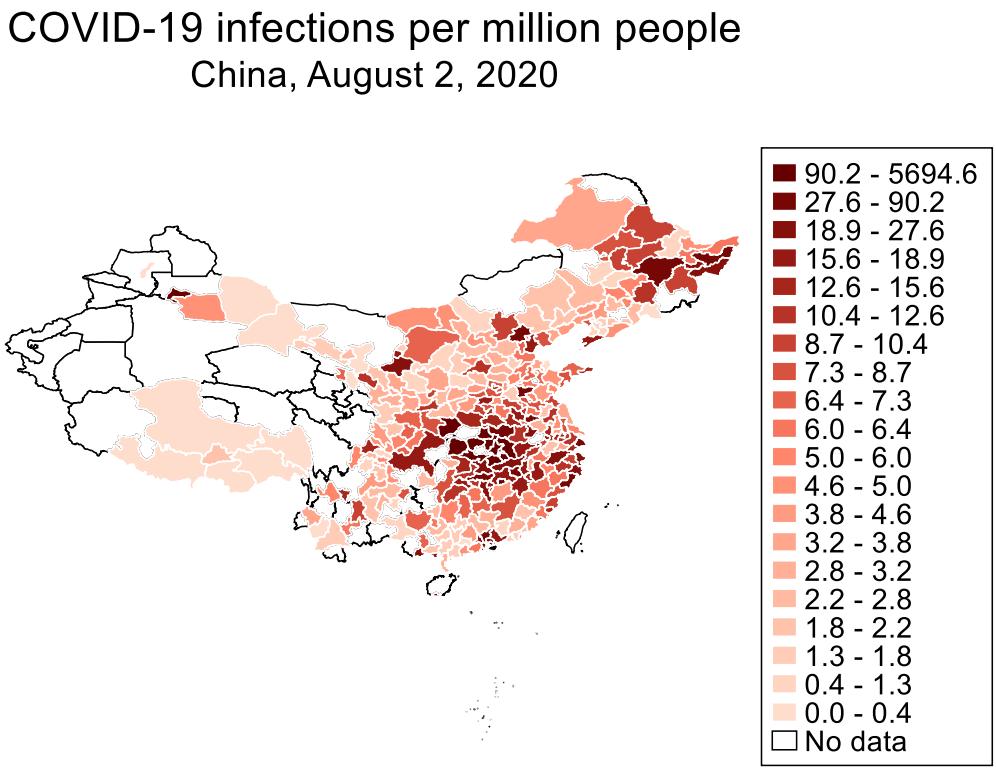


Figure A3 Geographical distribution of the prevalence of COVID-19 infections across cities
Note: As of August 2, 2020. Source: China Data Lab (http://dataverse.harvard.edu/dataverse/2019ncov); China City Statistical Yearbook 2019 (National Bureau of Statistics of China 2020)

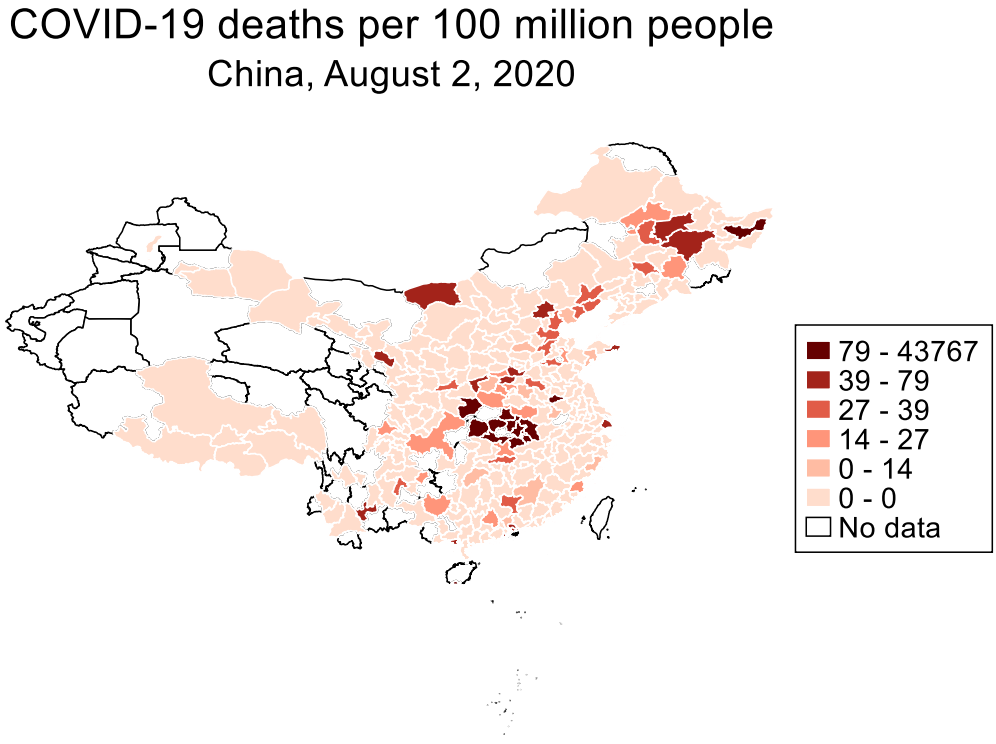


Figure A4 Geographical distribution of COVID-19 mortality across cities
Note: As of August 2, 2020. Source: China Data Lab (http://dataverse.harvard.edu/dataverse/2019ncov); China City Statistical Yearbook 2019 (National Bureau of Statistics of China 2020)

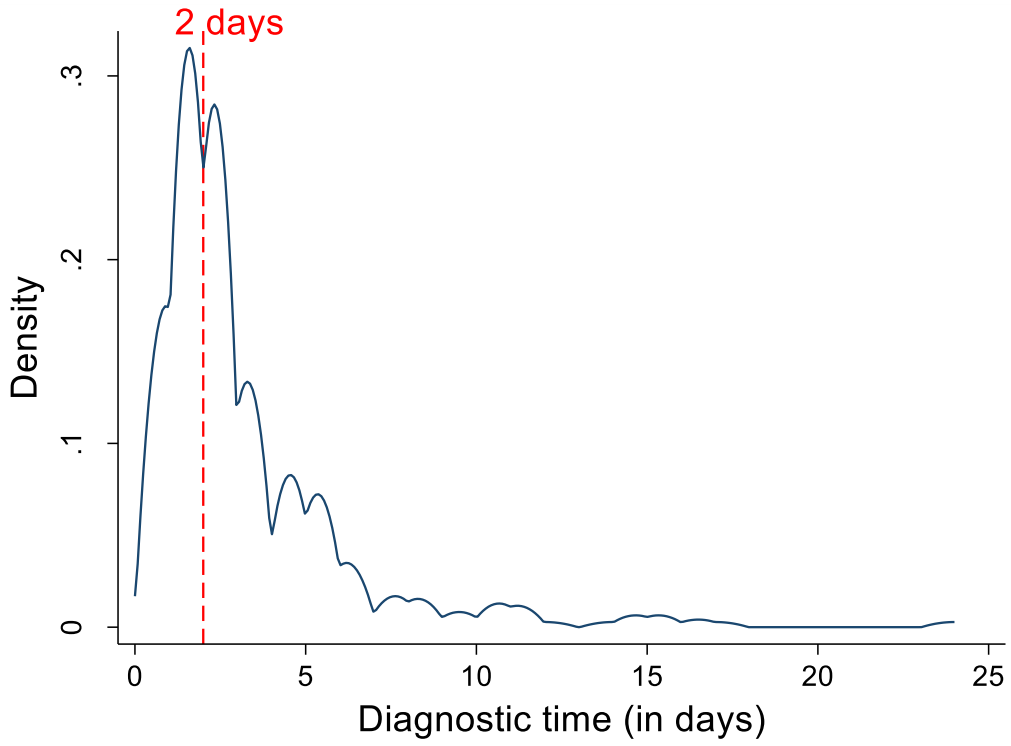


Figure A5 Density of diagnostic time distribution

Note: The dashed line represents the median value of diagnostic time in the sample. Sample size = 275. Diagnostic time = the time interval between the date of first visiting a doctor and the date of diagnostic confirmation to the public.

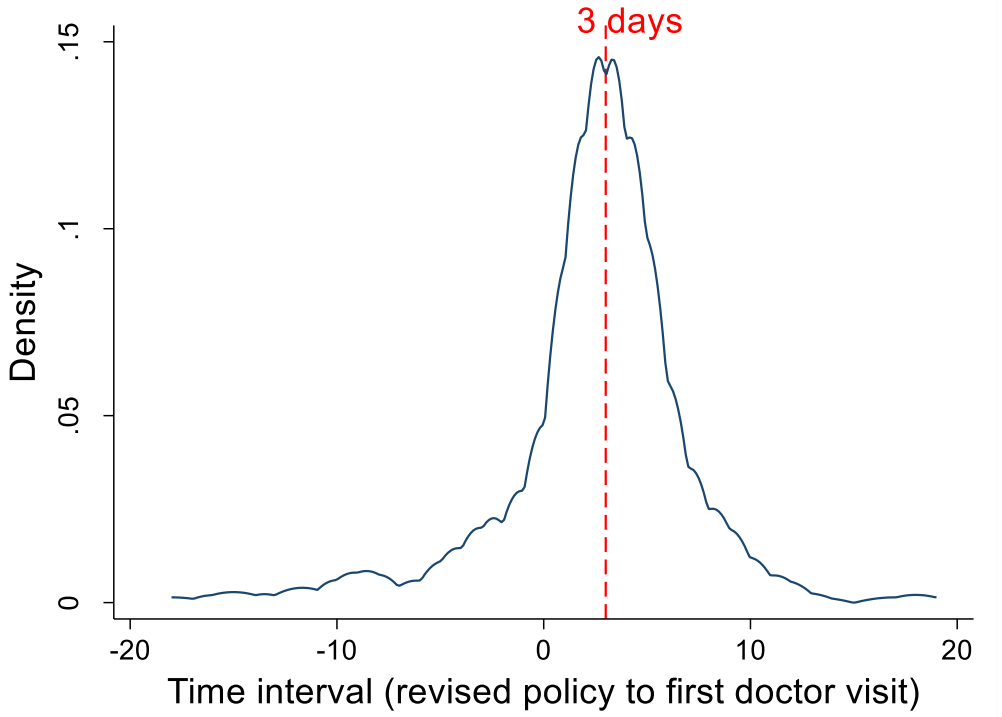


Figure A6 Density of time interval (revised policy to first doctor visit) distribution

Note: The dashed line represents the median value of time interval (revised policy to first doctor visit) in the sample. Sample size = 275. Time interval (revised policy to first doctor visit) = the time interval between the date when the local government adopted the updated official guidance (Version 2) on diagnostic confirmation for the first case outside Hubei province and the first diagnosed patient's date of first visiting a doctor.

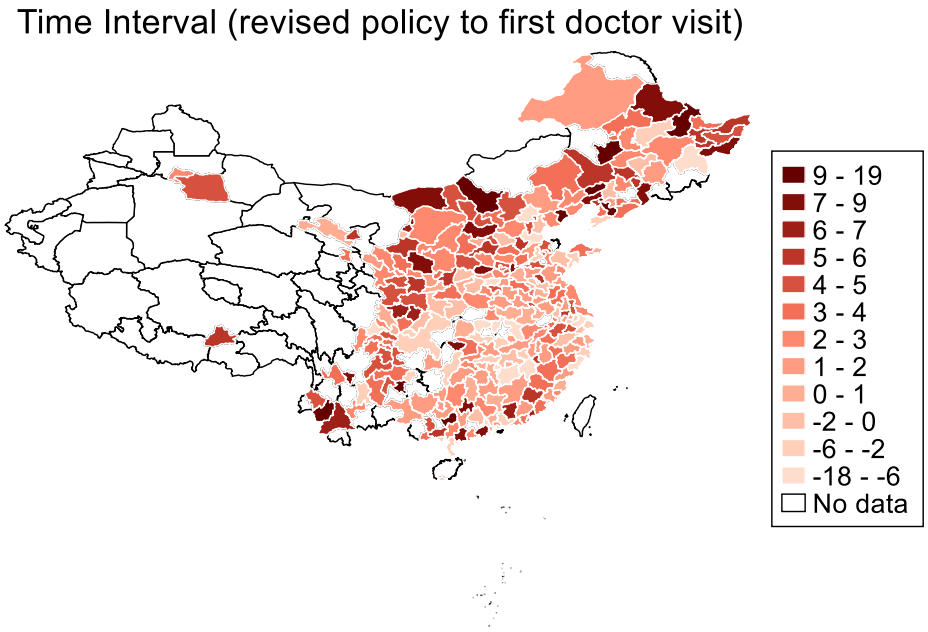


Figure A7 Geographical location of time interval (revised policy to first doctor visit) distribution

Note: Time interval (revised policy to first doctor visit) = the time interval between the date when the local government adopted the updated official guidance (Version 2) on diagnostic confirmation for the first case outside Hubei province and the first diagnosed patient's date of first visiting a doctor.

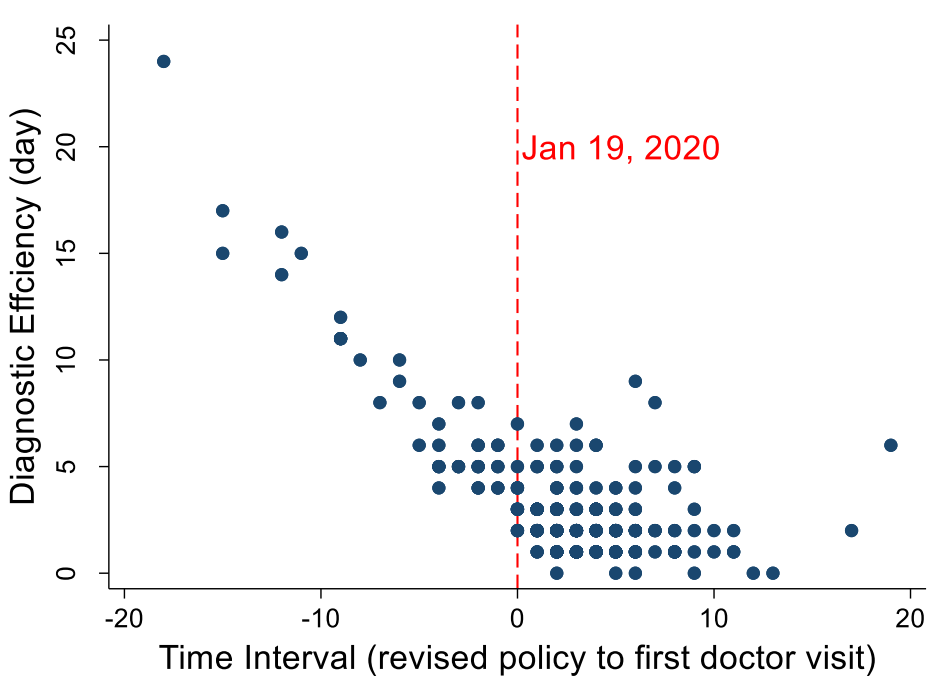


Figure A8 Diagnostic time and time interval (revised policy to first doctor visit) across 275 cities

Note: Diagnostic time = the time interval between the date of first visiting a doctor and the date of diagnostic confirmation to the public. Time interval (revised policy to first doctor visit) = the time interval between the date when the local government adopted the updated official guidance (Version 2) on diagnostic confirmation for the first case outside Hubei province and the first diagnosed patient's date of first visiting a doctor.

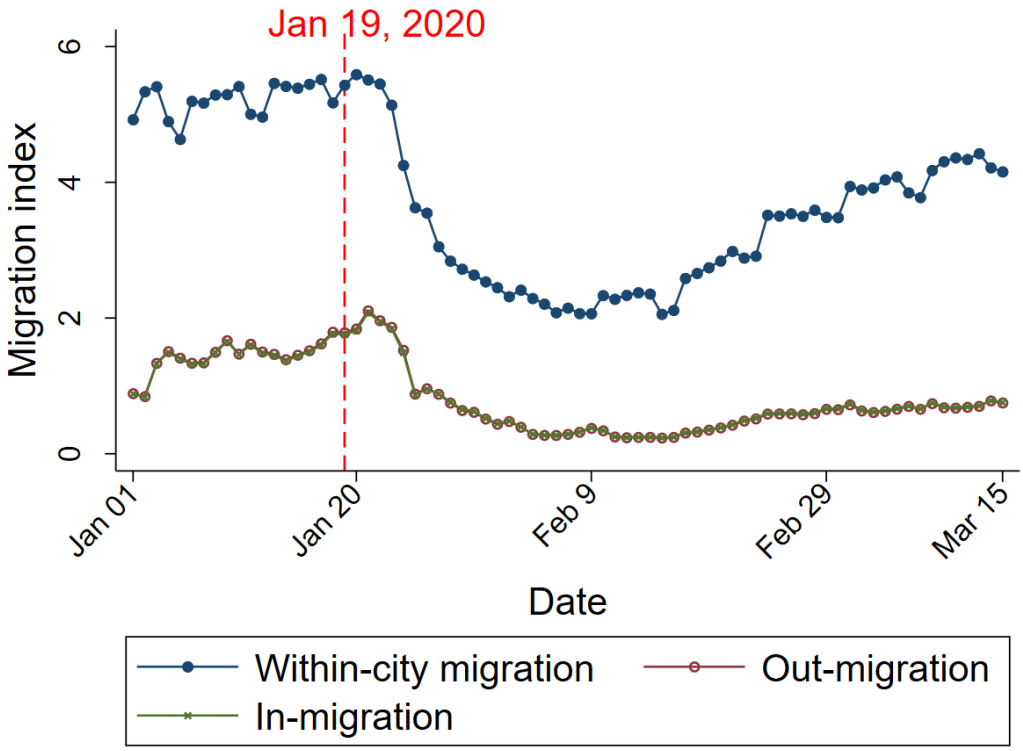


Figure A9 City-level travel intensity (migration indexes) on average from January 01, 2020, to March 15, 2020

Note: All daily migration indexes comes from Baidu Migration data between January 1, 2020, and March 15, 2020. Within-city migration index = travel intensity within cities. Out-migration index = travel intensity to other cities. In-migration index = travel intensity from other cities. These indicators are consistent across cities and across time.

B: Details for the OLS and IV estimates

Table A1 Impact of diagnostic time on prevalence of COVID-19 infections

Variables	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) IV	(9) First Stage
Diagnostic time (days)	0.14	0.03	0.03	0.03	0.01	0.00	0.00	0.09	
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Logarithm of travel time to the COVID-19 epicenter		-0.61	-0.61	-0.79	-1.00	-0.79	-0.62	-0.62	0.57
		(0.10)	(0.10)	(0.11)	(0.11)	(0.12)	(0.22)	(0.22)	(0.60)
Percentage of migrants from the COVID-19 epicenter (2015)		6.37	5.71	5.04	4.15	4.32	2.44	1.46	5.62
		(0.77)	(0.74)	(0.74)	(0.73)	(1.19)	(0.80)	(0.80)	(2.12)
Logarithm of GRP per capita (2018)			0.64	0.96	0.51	0.58	0.58	0.63	-0.76
			(0.11)	(0.16)	(0.18)	(0.18)	(0.21)	(0.20)	(0.57)
Percentage of secondary industry in GRP (2018)				-0.04	-0.02	-0.02	-0.01	-0.01	0.01
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Percentage of tertiary industry in GRP (2018)				-0.02	-0.01	-0.01	-0.00	-0.00	-0.06
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
Logarithm of hospital beds per thousand people (2018)					0.96	0.93	0.96	0.89	0.13
					(0.26)	(0.26)	(0.32)	(0.31)	(0.86)
Logarithm of public health staff per thousand people (2018)					0.00	-0.15	-0.28	-0.37	0.25
					(0.33)	(0.32)	(0.34)	(0.34)	(0.93)
Utilization of health systems (total patients) (%) (2020)					-0.01	-0.00			
					(0.01)	(0.01)			
Utilization of health systems (discharged patients) (%) (2020)					-0.01	-0.01			
					(0.01)	(0.00)			
Time interval (first case to public health alert)						0.06			
						(0.07)			
Time interval (revised policy to first doctor visit)									-0.51
									(0.03)
Observations	275	274	273	273	272	262	272	272	272
R-squared	0.11	0.44	0.50	0.53	0.60	0.44	0.73	0.71	0.64
F-stat	34.56	71.23	67.96	50.13	39.42	17.66	16.98	15.63	11.12
Weak identification test (Cragg-Donald Wald F statistic)	.z	.z	.z	.z	.z	.z	.z	237.05	.z
Endogeneity test of endogenous regressors (p-value)	.z	.z	.z	.z	.z	.z	.z	0.00	.z
Province dummies	No	No	No	No	No	No	Yes	Yes	Yes

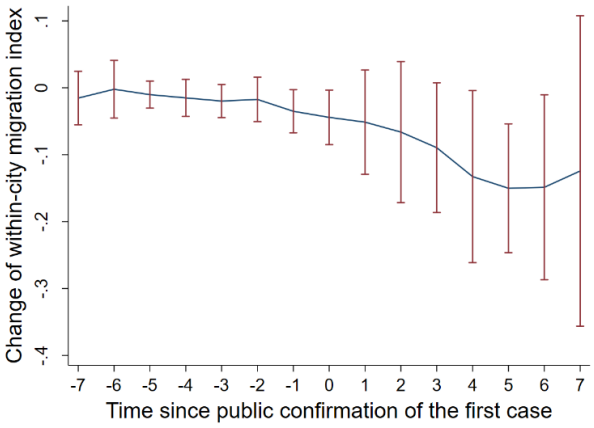
Note: This table reports the estimated impact of diagnostic time on prevalence of COVID-19 infections (the logarithm of COVID-19 prevalence). Columns 1–7 report OLS estimates. Columns 8 and 9 report IV estimates and first-stage results, respectively. Standard errors are in parentheses.

Table A2 Impact of diagnostic time on mortality of COVID-19

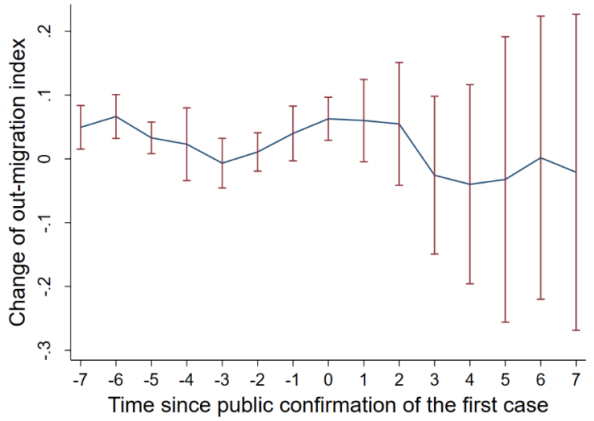
Variables	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) IV	(9) First Stage
Diagnostic time (days)	0.20	0.05	0.05	0.05	0.03	0.02	0.03	0.12	
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	
Logarithm of travel time to the COVID-19 epicenter		-0.35	-0.34	-0.58	-0.75	-0.15	-0.27	-0.28	0.57
		(0.16)	(0.16)	(0.18)	(0.19)	(0.20)	(0.39)	(0.37)	(0.60)
Percentage of migrants from the COVID-19 epicenter (2015)		10.06	9.98	9.02	7.53	4.67	2.81	1.78	5.62
		(1.20)	(1.22)	(1.24)	(1.28)	(1.98)	(1.42)	(1.37)	(2.12)
Logarithm of GRP per capita (2018)			0.09	0.68	0.25	0.49	0.95	1.00	-0.76
			(0.18)	(0.27)	(0.31)	(0.29)	(0.37)	(0.35)	(0.57)
Percentage of secondary industry in GRP (2018)				-0.06	-0.04	-0.04	-0.03	-0.03	0.01
				(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Percentage of tertiary industry in GRP (2018)				-0.05	-0.03	-0.02	-0.01	-0.01	-0.06
				(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)
Logarithm of hospital beds per thousand people (2018)					0.42	0.28	0.18	0.11	0.13
					(0.46)	(0.43)	(0.57)	(0.54)	(0.86)
Logarithm of public health staff per thousand people (2018)					0.23	0.08	-0.18	-0.28	0.25
					(0.57)	(0.53)	(0.61)	(0.58)	(0.93)
Utilization of health systems (total patients) (%) (2020)					-0.02	0.01			
					(0.01)	(0.01)			
Utilization of health systems (discharged patients) (%) (2020)					-0.02	-0.02			
					(0.01)	(0.01)			
Time interval (first case to public health alert)						0.36			
						(0.12)			
Time interval (revised policy to first doctor visit)									-0.51
									(0.03)
Observations	275	274	273	273	272	262	272	272	272
R-squared	0.10	0.34	0.34	0.37	0.42	0.19	0.60	0.58	0.64
F-stat	30.42	47.27	35.19	26.07	18.96	5.40	9.07	8.91	11.12
Weak identification test (Cragg-Donald Wald F statistic)	.z	.z	.z	.z	.z	.z	.z	237.05	.z
Province dummies	No	No	No	No	No	No	Yes	Yes	Yes

Note: This table reports the estimated impact of diagnostic time on mortality of COVID-19 (the logarithm of COVID-19 mortality). Columns 1–7 report OLS estimates. Columns 8 and 9 report IV estimates and first-stage results, respectively. Standard errors are in parentheses.

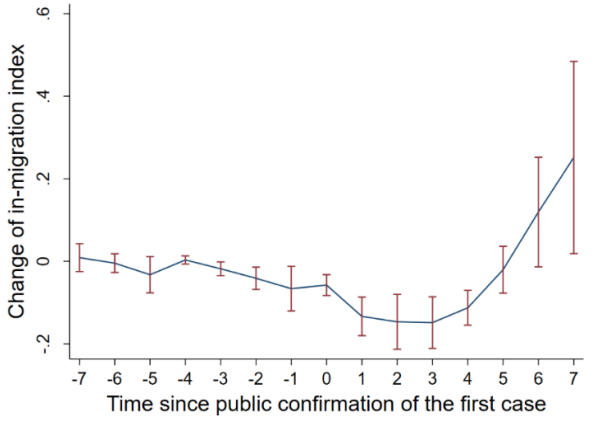
C: Placebo analysis of the impact of confirming the first case publicly on travel intensity in 2019



(a)



(b)



(c)

Figure A10. Placebo analysis of the impact of public confirmation of the first case on intra-city and inter-city travel intensity using Baidu Migration data in 2019

Note: All daily travel intensity data come from Baidu Migration data between January 1, 2019, and March 15, 2019. (a) Placebo analysis of the impact of public confirmation of the first case on intra-city travel intensity using Baidu Migration data in 2019. Within-city migration index = travel intensity within cities. These indicators are consistent across cities and across time. (b) Placebo analysis of the impact of public confirmation of the first case on travel intensity to other cities using Baidu Migration data in 2019. Out-migration index = travel intensity to other cities. These indicators are consistent across cities and across time. (c) Placebo analysis of the impact of public confirmation of the first case on travel intensity from other cities using Baidu Migration data in 2019. In-migration index = travel intensity from other cities. These indicators are consistent across cities and across time.

D: Heterogeneous impacts of diagnostic time over time

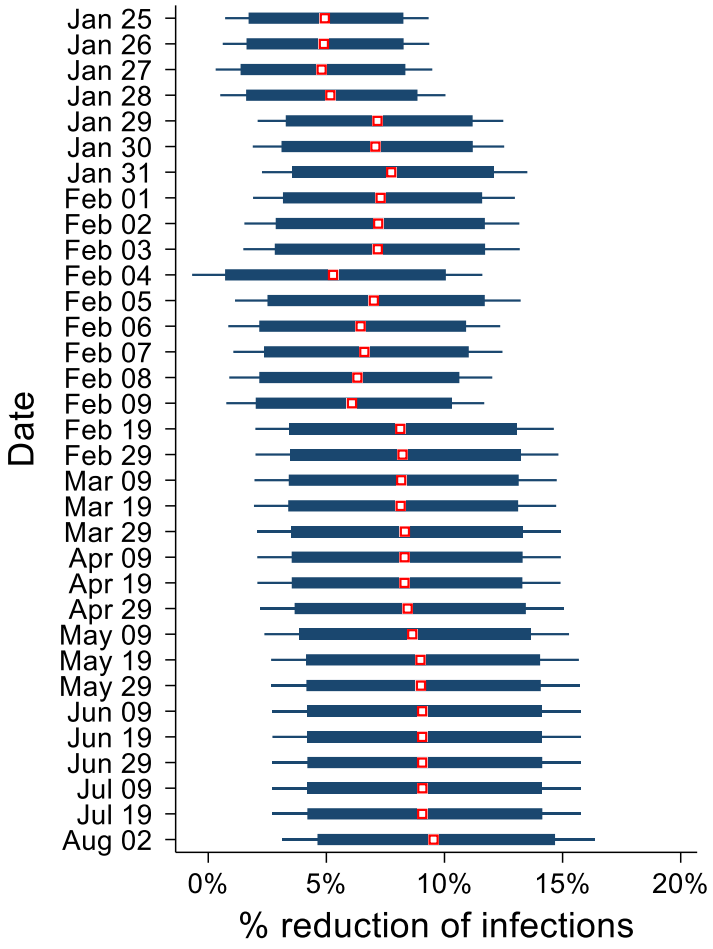


Figure A11 Impact of diagnostic time on the prevalence of COVID-19 infections over time

Note: Following the same IV approach, we estimate the impact of diagnostic time by day from January 25 to August 2, 2020. Diagnostic time = the time interval between the date of first visiting a doctor and the date of diagnostic confirmation to the public.

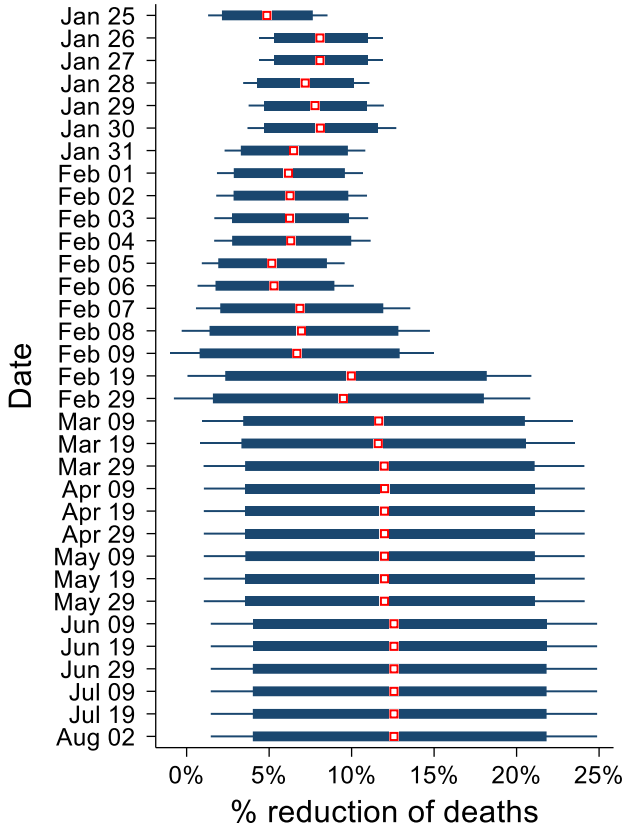


Figure A12 Impact of diagnostic time on COVID-19 mortality over time

Note: Following the same IV approach, we estimate the impact of diagnostic time by day from January 25 to August 2, 2020. Diagnostic time = the time interval between the date of first visiting a doctor and the date of diagnostic confirmation to the public.

E: Robustness Checks

Table A3 Robustness checks of the impacts of diagnostic time on prevalence of COVID-19 infections

Variables	(1) Control for the timing of infection	(2) Time interval (revised policy to first doctor visit) [-7,7]	(3) Time interval (revised policy to first doctor visit) [-6,6]	(4) Time interval (revised policy to first doctor visit) [-5,5]	(5) Time interval (revised policy to first doctor visit) [-4,4]	(6) Drop first case at the provincial level	(7) Drop cities of Hubei province	(8) Keep cities that imported the first case from the COVID-19 epicenter
Diagnostic time (days)	0.07	0.12	0.09	0.11	0.12	0.10	0.10	0.08
	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)
Relative timing of infection	0.01							
	(0.02)							
Logarithm of travel time to the	-0.65	-0.68	-0.63	-0.67	-0.76	-0.71	-0.80	-0.80
COVID-19 epicenter	(0.24)	(0.23)	(0.22)	(0.22)	(0.23)	(0.23)	(0.25)	(0.23)
Percentage of migrants from the	3.64	1.33	1.39	1.10	0.83	1.45	3.15	3.27
COVID-19 epicenter (2015)	(1.18)	(0.89)	(0.85)	(0.85)	(0.88)	(0.94)	(1.19)	(1.13)
Logarithm of GRP per capita	0.53	0.64	0.73	0.81	0.70	0.51	0.62	0.57
(2018)	(0.20)	(0.21)	(0.20)	(0.21)	(0.23)	(0.22)	(0.21)	(0.21)
Percentage of secondary	-0.01	-0.02	-0.02	-0.03	-0.02	-0.00	-0.01	-0.02
industry in GRP (2018)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Percentage of tertiary industry	-0.01	-0.01	-0.01	-0.01	-0.01	0.01	-0.00	-0.01
in GRP (2018)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Logarithm of hospital beds per	0.88	0.82	0.76	0.86	0.68	1.01	0.89	0.71
thousand people (2018)	(0.31)	(0.32)	(0.31)	(0.32)	(0.35)	(0.33)	(0.32)	(0.32)
Logarithm of public health staff	-0.28	-0.28	-0.33	-0.39	-0.14	-0.33	-0.48	-0.13
per thousand people (2018)	(0.34)	(0.35)	(0.33)	(0.34)	(0.39)	(0.36)	(0.34)	(0.35)
Observations	240	237	230	210	182	246	262	240
R-squared	0.65	0.68	0.70	0.72	0.73	0.70	0.55	0.65
F-stat	10.12	11.72	12.74	13.02	11.59	14.74	8.32	11.01
Cragg-Donald Wald F statistic	102.74	101.39	136.75	122.00	87.02	127.85	169.46	247.44
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports robustness checks of the impacts of diagnostic time on prevalence of COVID-19 infections (the logarithm of COVID-19 prevalence) using the IV approach. Column 1 reports main results by controlling for the relative timing of infection. Columns 2–5 report main results by focusing on cities exposed to similar dates of the first case's first visit to a doctor with different cutoffs. Column 6 reports main results by dropping those cities that confirm the first infected case at the provincial level. Column 7 reports main results by dropping cities of Hubei province. Column 8 reports main results by keeping those cities that are known to have imported the first COVID-19 case. Diagnostic time = the time interval between the date of first visiting a doctor and the date of diagnostic confirmation to the public. Standard errors are in parentheses.

Table A4 Robustness checks on the impacts of diagnostic time on COVID-19 mortality

Variables	(1) Control for the timing of infection	(2) Time interval (revised policy to first doctor visit) [-7,7]	(3) Time interval (revised policy to first doctor visit) [-6,6]	(4) Time interval (revised policy to first doctor visit) [-5,5]	(5) Time interval (revised policy to first doctor visit) [-4,4]	(6) Drop first case at the provincial level	(7) Drop cities of Hubei province	(8) Keep cities that imported the first case from the COVID-19 epicenter
Diagnostic time (days)	0.12	0.11	0.10	0.05	0.05	0.13	0.13	0.10
	(0.07)	(0.08)	(0.08)	(0.09)	(0.10)	(0.05)	(0.05)	(0.05)
Relative timing of infection	0.02							
	(0.03)							
Logarithm of travel time to the	-0.29	-0.37	-0.34	-0.29	-0.14	-0.26	-0.33	-0.58
COVID-19 epicenter	(0.43)	(0.40)	(0.41)	(0.40)	(0.43)	(0.38)	(0.42)	(0.42)
Percentage of migrants from the	4.00	1.50	1.48	1.54	1.55	1.39	4.14	4.99
COVID-19 epicenter (2015)	(2.14)	(1.55)	(1.57)	(1.55)	(1.62)	(1.52)	(2.06)	(2.01)
Logarithm of GRP per capita	0.85	1.07	1.15	1.14	1.20	0.66	0.94	0.82
(2018)	(0.37)	(0.36)	(0.38)	(0.38)	(0.43)	(0.36)	(0.36)	(0.37)
Percentage of secondary	-0.03	-0.05	-0.05	-0.04	-0.05	-0.02	-0.03	-0.04
industry in GRP (2018)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Percentage of tertiary industry	-0.01	-0.03	-0.03	-0.02	-0.02	-0.00	-0.01	-0.02
in GRP (2018)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)
Logarithm of hospital beds per	0.45	0.28	0.21	0.04	-0.10	0.25	0.06	0.16
thousand people (2018)	(0.57)	(0.56)	(0.58)	(0.58)	(0.65)	(0.53)	(0.55)	(0.57)
Logarithm of public health staff	-0.44	-0.25	-0.29	-0.15	-0.20	-0.37	-0.34	-0.22
per thousand people (2018)	(0.61)	(0.60)	(0.62)	(0.62)	(0.71)	(0.58)	(0.59)	(0.62)
Observations	240	237	230	210	182	246	262	240
R-squared	0.41	0.56	0.55	0.60	0.61	0.62	0.30	0.46
F-stat	3.98	6.74	6.56	7.14	6.25	10.31	2.97	4.96
Cragg-Donald Wald F statistic	102.74	101.39	136.75	122.00	87.02	127.85	169.46	247.44
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports robustness checks of the impacts of diagnostic time on COVID-19 mortality (the logarithm of COVID-19 mortality) using the IV approach. Column 1 reports main results by controlling for the relative timing of infection. Columns 2–5 report main results by focusing on cities exposed to similar dates of the first case's first visit to a doctor with different cutoffs. Column 6 reports main results by dropping those cities that confirm the first infected case at the provincial level. Column 7 reports main results by dropping cities of Hubei province. Column 8 reports main results by keeping those cities that are known to have imported the first COVID-19 case. Diagnostic time = the time interval between the date of first visiting a doctor and the date of diagnostic confirmation to the public. Standard errors are in parentheses.

Table A5 Impacts of the instrumental variable on the prevalence of diseases

Variables	(1) Prevalence of influenza in 2018	(2) Prevalence of_COVID-19
Time interval (revised policy to first doctor visit)	0.01	-0.05
	(0.01)	(0.01)
Logarithm of travel time to the COVID-19 epicenter	-0.12	-0.57
	(0.27)	(0.21)
Percentage of migrants from the COVID-19 epicenter (2015)	0.82	1.97
	(0.95)	(0.76)
Logarithm of gross regional product per capita (2018)	-0.29	0.56
	(0.26)	(0.20)
Percentage of secondary industry in GRP (2018)	0.00	-0.01
	(0.02)	(0.01)
Percentage of tertiary industry in GRP (2018)	0.01	-0.01
	(0.02)	(0.01)
Logarithm of hospital beds per thousand people (2018)	0.50	0.90
	(0.39)	(0.31)
Logarithm of public health staff per thousand people (2018)	0.92	-0.35
	(0.42)	(0.33)
Observations	251	272
R-squared	0.68	0.75
F-stat	11.62	18.49
Province dummies	Yes	Yes

Note: this table reports robustness checks of the impact of the instrumental variable on the prevalence of diseases using the OLS approach. Column 1 reports the impact of the instrumental variable on the logarithm of the prevalence of influenza in 2018. Column 2 reports the impact of the instrumental variable on the logarithm of the prevalence of the COVID-19. Standard errors are in parentheses.

Table A6 Test the instrument validity regarding COVID-19 prevalence

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample		Time interval (revised policy to first doctor visit) [-7,7]		Time interval (revised policy to first doctor visit) [-6,6]		Time interval (revised policy to first doctor visit) [-5,5]		Time interval (revised policy to first doctor visit) [-4,4]	
	New IV	All IVs	New IV	All IVs	New IV	All IVs	New IV	All IVs	New IV	All IVs
Diagnostic time (day)	0.06	0.08	0.08	0.10	0.08	0.09	0.09	0.10	0.10	0.12
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)
Logarithm of travel time to the COVID-19 epicenter	-0.62	-0.62	-0.67	-0.67	-0.63	-0.63	-0.66	-0.67	-0.75	-0.76
	(0.21)	(0.21)	(0.23)	(0.23)	(0.22)	(0.22)	(0.22)	(0.22)	(0.23)	(0.23)
Percentage of migrants from the COVID-19 epicenter (2015)	1.86	1.61	1.46	1.41	1.44	1.41	1.18	1.13	0.94	0.87
	(0.78)	(0.78)	(0.87)	(0.87)	(0.84)	(0.84)	(0.84)	(0.84)	(0.88)	(0.88)
Logarithm of gross regional product per capita (2018)	0.61	0.62	0.65	0.65	0.73	0.73	0.82	0.81	0.72	0.70
	(0.20)	(0.20)	(0.20)	(0.21)	(0.20)	(0.20)	(0.21)	(0.21)	(0.23)	(0.23)
Percentage of secondary industry in GRP (2018)	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Percentage of tertiary industry in GRP (2018)	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Logarithm of hospital beds per thousand people (2018)	0.92	0.90	0.81	0.82	0.76	0.76	0.87	0.86	0.69	0.68
	(0.30)	(0.31)	(0.31)	(0.32)	(0.31)	(0.31)	(0.32)	(0.32)	(0.35)	(0.35)
Logarithm of public health staff per thousand people (2018)	-0.33	-0.36	-0.26	-0.27	-0.32	-0.32	-0.37	-0.38	-0.14	-0.14
	(0.32)	(0.33)	(0.34)	(0.34)	(0.33)	(0.33)	(0.34)	(0.34)	(0.38)	(0.39)
Observations	272	272	237	237	230	230	210	210	182	182
R-squared	0.72	0.71	0.69	0.69	0.71	0.71	0.73	0.73	0.74	0.74
F-stat	16.46	16.01	12.24	12.04	12.88	12.81	13.25	13.12	11.86	11.70
Cragg-Donald Wald F statistic	173.39	145.51	113.13	67.21	121.33	81.33	100.69	68.77	72.11	47.41
Overidentification test of all instruments (p-value)	.	0.0662	.	0.2808	.	0.6688	.	0.5592	.	0.5444
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: this table reports the impact of diagnostic time on prevalence of COVID-19 infections using two different IVs. Columns 1–2 report results using all cities. Columns 2–5 report main results by focusing on cities exposed to similar dates of the first case's first visit to a doctor with different cutoffs. The new IV refers to a dummy variable indicating whether or not the first case's first visit to a doctor after January 18, 2020, when more efficient diagnostic technologies and process became available. Standard errors are in parentheses.

Table A7 Test the instrument validity regarding COVID-19 mortality

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample		Time interval (revised policy to first doctor visit) [-7,7]		Time interval (revised policy to first doctor visit) [-6,6]		Time interval (revised policy to first doctor visit) [-5,5]		Time interval (revised policy to first doctor visit) [-4,4]	
	New IV	All IVs	New IV	All IVs	New IV	All IVs	New IV	All IVs	New IV	All IVs
Diagnostic time (day)	0.07	0.10	0.05	0.07	0.04	0.08	0.01	0.04	0.01	0.03
	(0.04)	(0.04)	(0.08)	(0.07)	(0.08)	(0.07)	(0.09)	(0.08)	(0.11)	(0.10)
Logarithm of travel time to the	-0.27	-0.28	-0.35	-0.36	-0.32	-0.33	-0.28	-0.29	-0.12	-0.13
COVID-19 epicenter	(0.37)	(0.37)	(0.40)	(0.40)	(0.40)	(0.41)	(0.40)	(0.40)	(0.42)	(0.42)
Percentage of migrants from the	2.37	2.00	1.76	1.64	1.72	1.59	1.72	1.61	1.75	1.62
COVID-19 epicenter (2015)	(1.37)	(1.36)	(1.53)	(1.53)	(1.55)	(1.55)	(1.54)	(1.54)	(1.62)	(1.61)
Logarithm of gross regional	0.97	0.99	1.09	1.08	1.16	1.15	1.17	1.15	1.24	1.21
product per capita (2018)	(0.35)	(0.35)	(0.36)	(0.36)	(0.37)	(0.37)	(0.38)	(0.38)	(0.43)	(0.43)
Percentage of secondary industry	-0.03	-0.03	-0.05	-0.05	-0.06	-0.05	-0.05	-0.05	-0.06	-0.05
in GRP (2018)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Percentage of tertiary industry in	-0.01	-0.01	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.02	-0.02
GRP (2018)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Logarithm of hospital beds per	0.15	0.12	0.27	0.27	0.21	0.21	0.05	0.04	-0.08	-0.09
thousand people (2018)	(0.53)	(0.53)	(0.55)	(0.55)	(0.57)	(0.57)	(0.58)	(0.58)	(0.65)	(0.65)
Logarithm of public health staff	-0.22	-0.26	-0.21	-0.23	-0.26	-0.28	-0.11	-0.14	-0.18	-0.19
per thousand people (2018)	(0.57)	(0.57)	(0.59)	(0.60)	(0.61)	(0.61)	(0.62)	(0.62)	(0.71)	(0.71)
Observations	272	272	237	237	230	230	210	210	182	182
R-squared	0.59	0.59	0.57	0.56	0.56	0.56	0.60	0.60	0.61	0.61
F-stat	9.04	8.99	6.89	6.83	6.67	6.62	7.22	7.18	6.33	6.28
Cragg-Donald Wald F statistic	173.39	145.51	113.13	67.21	121.33	81.33	100.69	68.77	72.11	47.41
Overidentification test of all instruments (p-value)	.	0.1204	.	0.2434	.	0.2614	.	0.4640	.	0.5312
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: this table reports the impact of diagnostic time on COVID-19 mortality using two different IVs. Columns 1–2 report results using all cities. Columns 2–5 report main results by focusing on cities exposed to similar dates of the first case's first visit to a doctor with different cutoffs. The new IV refers to a dummy variable indicating whether or not the first case's first visit to a doctor after January 18, 2020, when more efficient diagnostic technologies and process became available. Standard errors are in parentheses.