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ABSTRACT

Act Early to Prevent Infections and Save Lives: Causal Impact of Diagnostic Efficiency on the COVID-19 Pandemic*

This paper examines the impact of diagnostic efficiency on the COVID-19 pandemic. Using an exogenous policy on diagnostic confirmation, we show that a one- day decrease in the time taken to confirm the first case in a city publicly led to 9.4% and 12.7% reductions in COVID-19 prevalence and mortality over the subsequent six months, respectively. The impact is larger for cities that are farther from the COVID-19 epicenter, are exposed to less migration, and have more responsive public health systems. Social distancing and a less burdened health system are likely the underlying mechanisms, while the latter also explains the more profound impact on reducing deaths than reducing infections.

JEL Classification: D83, H75, I12, I18, J61

Keywords: diagnostic efficiency, information disclosure, social distancing, COVID-19, China, instrumental variable

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1 Introduction

The coronavirus disease 2019 (COVID-19) pandemic has inflicted substantial death tolls across the globe. As of the end of September, 2020, over 30 million COVID-19 cases had been confirmed in more than 210 countries and territories and upwards of 1 million individuals had lost their lives to the disease.[2] Many countries have taken unprecedented measures (e.g., city-wide lockdowns, travel restrictions) to contain the spread of COVID-19 (Aum, Lee, and Shin 2020; Briscese et al. 2020; S. Chen, Yang, et al. 2020; S. Chen, Zhang, et al. 2020). While these measures may have some mitigating effects on the transmission and impact of COVID-19, they also impose grave social and economic burdens on society (Adda 2016; Alvarez, Argente, and Lippi 2020; Acemoglu et al. 2020; Do et al. 2020).

However, public health responses in the early phase of COVID-19, such as efficient diagnosis and isolation, could potentially have had a large impact on reducing disease transmission while preempting the need for more economically and socially harmful interventions.[3] But to what extent "early" intervention policies help to contain the spread of COVID-19 remains unclear.

One such policy, diagnostic efficiency—which we define as the time it takes for a particular city to diagnose and publicly announce its first COVID-19 case—is a key signal of a government's awareness of the disease and willingness to disclose relevant information. A more efficient diagnostic process allows early behavioral and policy response to an outbreak, which may shorten the length of lockdown periods, leading to several notable advantages compared with long-term nationwide lockdown and travel restrictions. First, it can avert more infections and deaths. Modeling studies show that responding to an outbreak early could prevent more infections than otherwise (Berger, Herkenhoff, and Mongey 2020; Chudik, Pesaran, and Rebucci 2020; Eichenbaum, Rebelo, and Trabandt 2020; S. Chen, Chen, et al. 2020). Second, it can mitigate the negative social effects (e.g., massive protests) of long-term lockdowns and social

[2] COVID-19 data are provided by the Center for Systems Science and Engineering at Johns Hopkins University. More details and updated data can be found in https://coronavirus.jhu.edu/map.html.

[3] A wide range of nonpharmaceutical interventions in the early phase of COVID-19 include genome sequencing for the novel virus, prompt development of diagnostics, timely information disclosure of the number of infections and deaths, social distancing, contact tracing, massive testing, quarantine of suspected cases and close contacts, and isolation of cases.

distancing (Dyer 2020).[4] Third, by enabling early announcement of a novel infectious disease with the potential to become an epidemic, early intervention against it, and its speedy termination, a more efficient diagnostic process can help reduce the heavy economic toll of long-term lockdowns (Aum, Lee, and Shin 2020; Acemoglu et al. 2020; Alvarez, Argente, and Lippi 2020). All these advantages suggest that a more efficient diagnostic process could be a highly cost-effective measure when facing an epidemic.

Improved diagnostic efficiency helps limit infections and deaths through the following channels: First, it enables early voluntary or mandatory isolation of infected individuals from the community (Omar et al. 2020; S. Chen, Zhang, et al. 2020). Second, it informs the public of the disease, allowing local residents to initiate preventive measures against COVID-19 such as wearing masks, frequently washing hands, or social distancing (Chan and Yuen 2020; Cheng et al. 2020; Feng et al. 2020). Third, local authorities can implement outbreak-control interventions such as contact tracing, disease screening, and encouragement of mask wearing (Anderson et al. 2020; S. Chen, Yang, et al. 2020; Kraemer et al. 2020).[5] Fourth, it can avoid the danger of overburdening health systems by reducing infections and rapidly expanding health system capacities, thus ensuring sufficient healthcare resources such as intensive care unit (ICU) beds and ventilators to save lives (Armocida et al. 2020; Cavallo, Donoho, and Forman 2020; Woolley 2020; S. Chen, Zhang, et al. 2020; Ji et al. 2020). Finally, important actors in other societal sectors (e.g., academic institutions, companies, and media outlets) can also take early action (Ranney, Griffeth, and Jha 2020; Simonov et al. 2020; Bavel et al. 2020).[6]

Whether, to what extent, and how diagnostic efficiency affects the epidemic trend remain unknown. Improved diagnostic efficiency, on the one hand, could prevent

[4] Reportedly, people in many countries such as the United States, the United Kingdom, and Germany have protested against lockdown measures and social distancing rules (https://www.bbc.com/news/world-us-canada-52359100, https://www.reuters.com/article/us-health-coronavirus-germany-protests/germans-stage-protests-against-lockdown-measures-social-distancing-rules-idUSKBN22S0MS, https://www.abc.net.au/news/2020-05-17/protests-against-coronavirus-lockdown-in-uk-and-europe-covid-19/12256802).

[5] The proportion of people in each country who say they wear a face mask when in public varies significantly across countries. For example, more than 80% of people wore a face mask in China from February 24, 2020, to July 6, 2020. By contrast, less than 40%, 9%, and 7% of people wore a face mask during the same period in the United Kingdom, Norway, and Finland, respectively, during the same period. Countries like the United States and Italy saw fewer people wearing a face mask in the early period of the outbreak but the proportion increased gradually to 73% and 83% by July 6, 2020, respectively. More details on each country's mask wearing over time can be found in https://yougov.co.uk/topics/international/articles-reports/2020/03/17/personal-measures-taken-avoid-covid-19.

[6] 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.

infections and avert deaths if governments and people implement epidemic-control strategies early. On the other hand, it may have little impact on the epidemic trend if government and society remain inert and fail to respond to the warnings of a public health emergency. Only a few studies have investigated how diagnostic efficiency affects the spread of epidemics using mathematical modeling approaches (e.g., susceptible-exposed-infected-recovered-type models) (Chowell et al. 2015; Nouvellet et al. 2015; Rong et al. 2020). Harris (2020) proposes a nonparametric statistical method to estimate the distribution of reporting delays of confirmed COVID-19 cases in New York. These studies focus mainly on early diagnosis of all cases, rather than early diagnosis of the first case. Early diagnosis of all cases indicates a massive and rapid testing strategy, while early diagnosis of the first case reflects prompt public information disclosure of a novel infectious disease with the potential to become an epidemic, regardless of further interventions such as a massive testing strategy, contact tracing, or social distancing. Moreover, these studies do not show to what extent early diagnosis is effective in mitigating epidemics if government and society are not responsive.[7]

To our knowledge, this is the first empirical study to estimate the causal impact of diagnostic efficiency on epidemic spread. In this paper, we investigate whether and how diagnostic efficiency—measured by the time interval between the date when the first diagnosed patient first visited a doctor for COVID-19 care and the date when that first case was confirmed publicly—affected the spread of COVID-19 across 275 Chinese cities (**Figure 1**). Because factors such as patients' clinical manifestations, doctors' knowledge of COVID-19, adoption of different diagnostic technologies, and the regime for local health authorities' disclosure of COVID-19 cases can affect diagnostic efficiency, we adopt an instrumental variable (IV) approach to address confounding issues. We implement the IV approach by taking advantage of a plausibly exogenous nationwide policy that increases the availability of better diagnostic technology and streamlines the process by which local authorities report infected cases. We also construct a novel dataset on the first confirmed cases across 275 Chinese cities.

Our analysis exploits a plausibly exogenous policy launched by the central health

[7] Eichenbaum, Rebelo, and Trabandt (2020) suggest that testing without quarantining infected people can worsen the economic and health repercussions of an epidemic.

authority that improved the diagnostic efficiency of local health authorities in reporting their first confirmed local case. In general, for diseases that clinicians understand well (e.g., tuberculosis or human immunodeficiency virus), the time taken to diagnose any single case of that disease should be independent of the calendar date on which the diagnosed patient first sought care. However, for poorly understood emerging diseases for which knowledge and diagnostic technology are limited, the process of diagnosing the first case in any given location is often relatively complicated (relying on strict criteria) and lengthy. For example, evidence of a high degree of homology between the genetic sequence of a viral specimen collected from a patient and the genetic sequences of previously identified COVID-19 samples was required to confirm the first case of COVID-19 for localities with new transmission early in the epidemic. Moreover, local health authorities in China were not permitted to release information about first cases at the provincial level until the central health authority had verified their results.[8] This top-down information disclosure regime reduces the risk of misdiagnosis at the beginning of local outbreaks, but also lengthens the time required to verify first cases for local authorities.[9]

The diagnostic efficiency of confirming the first case significantly improved after January 18, when the central health authority released updated official guidance (Version 2) on diagnostic confirmation of the first case in each province experiencing new transmission outside of Hubei province, where COVID-19 was first reported in China (**Figure 1**).[10] This updated guidance indicated that a positive result for COVID-19 nucleic acid from real-time fluorescent polymerase chain reaction (PCR) (i.e., RT-PCR, a nuclear-derived method for detecting the presence of specific genetic material in any pathogen, including a virus) could serve as an alternative means of confirmation to the established method of determining that the viral gene sequence of a specimen from the diagnosed patient was highly homologous to known coronaviruses.[11] Introducing new diagnostic technology significantly shortened the time required to confirm the first infected case for other city-level health authorities, particularly after

[8] Similarly, city-level health authorities in China were not permitted to release information about first cases at the city level until the provincial health authority verified their results.

[9] An initial lack of point-of-care diagnostic kits further lengthened the overall duration.

[10] Further details on the updated official guidance are provided below.

[11] More details on the application of RT-PCR in detecting COVID-19 can be found in https://www.iaea.org/newscenter/news/how-is-the-covid-19-virus-detected-using-real-time-rt-pcr.

confirmation of the first provincial-level infected case.[12] Nevertheless, a trade-off exists between diagnostic efficiency and diagnostic accuracy.[13]

Our paper constructs an IV model based on the time interval between January 19, when the updated official guidance (Version 2) on diagnostic confirmation of the first case outside of Hubei province went into effect, and the date when the first diagnosed patient in a locality first visited a doctor, or *time interval (revised policy to first doctor visit)* for short (**Figure 1**).[14] The indicator builds on two developments: first, the first infected case outside Hubei province was not publicly confirmed until January 19, and second, the adoption of new diagnostic technology was limited to start because of a lack of point-of-care diagnostic kits—a situation that, however, improved over time.[15] An important assumption here is that, conditional on importing infected cases from the COVID-19 epicenter, the relative timing of the first case first visiting a doctor—or the time interval—is quasi-random and independent of the outcomes of interest. This assumption is likely to be true given that the incubation period can last for as long as 14 days following infection, meaning that the timing of the first visit to a doctor can vary significantly among the infected cases imported from the COVID-19 epicenter (World Health Organization 2020b).[16]

We report the main findings as follows. First, the average time taken to publicly confirm the first case in location jurisdictions fell significantly following the launch of the policy that improved diagnostic efficiency for local health authorities. Specifically, an increase

[12] Confirming the first provincial-level infected case still required evidence that the viral gene sequence is highly homologous to known coronaviruses; the central health authority undertook this confirmation.

[13] A systematic review of the accuracy of COVID-19 tests reported false negative rates between 2% and 29%, based on negative RT-PCR tests that were positive on repeat testing (Watson, Whiting, and Brush 2020; Arevalo-Rodriguez et al. 2020). Zhifeng, Feng, and Li (2020) also find that the initial nucleic acid positivity was not consistent with variations in lung computed tomography (CT). If the positivity of initial nucleic acid acts as the gold standard, the sensitivity of characteristic lung CT changes will be only 12%. If the characteristic lung CT changes are adopted as the gold standard, the sensitivity of the initial nucleic acid test will be 30.16%.

[14] The central health authority launched the policy on January 18, 2020, and all local health authorities adopted the new policy afterward. Moreover, according to the definition, if the first diagnosed patient first visited a doctor before (after) the new policy, then time interval (revised policy to first doctor visit) has a negative (positive) value.

[15] The former one suggests that launching the updated official guidance (Version 2) on diagnostic confirmation of the first case outside Hubei province provides a plausible source of exogenous variation in the timing of confirming the first case in a city publicly, while the latter one suggests that the gradual adoption of new diagnostic technology provides an alternative plausible source of exogenous variation in the timing of confirming publicly the first case in a city.

[16] Early epidemiological evidence shows that people with COVID-19 generally develop signs and symptoms on average 5–6 days after infection (mean incubation period 5–6 days, range 1–14 days). Later epidemiological evidence also suggests that the incubation period can be longer than 14 days (Li et al. 2020) and that some infected cases do not demonstrate any symptoms. We do not consider unreported cases in this paper due to data limitations. However, as China tests and counts all cases including asymptomatic cases (Long et al. 2020), we think this will have minor effect on our results.

of one standard deviation (4.5 days) in the value of time interval (revised policy to first doctor visit) led to a reduction of about 2 days on average in *diagnostic efficiency*. Second, using an instrumental variables approach, we find that a 1-day reduction in the time taken to confirm publicly the first case led to about 9.4% and 12.7% reductions in prevalence and mortality of COVID-19 on average over the subsequent six months, respectively, suggesting that improved diagnostic efficiency not only reduces infections but also saves lives and that the ordinary least squares (OLS) estimate (0% and 3% for prevalence and mortality of COVID-19, respectively) is underestimated. Third, the impact is more pronounced for cities farther from the COVID-19 epicenter (16% and 26% for prevalence and mortality of COVID-19, respectively), those exposed to relatively less migration prior to disease transmission (19% and 25% for prevalence and mortality of COVID-19, respectively), those with more responsive public health systems (26% and 25% for prevalence and mortality of COVID-19, respectively) and those with higher capacity utilization of health systems (13% and 20% for prevalence and mortality of COVID-19, respectively). Moreover, we show that publicly confirming the first case dramatically reduces intra-city travel intensity (13%), travel intensity to other cities (28%), and travel intensity from other cities (37%) for three days after the public announcement, suggesting that social distancing, induced by early public confirmation, is a possible underlying mechanism. A less stressed health system can explain the greater reduction in deaths than in infections. Finally, we show that all the impacts persist over time.

This paper fills a research gap on the causal impact of diagnostic efficiency on the spread of epidemics, complementing previous studies that use mathematical modeling approaches (Chowell et al. 2015; Nouvellet et al. 2015; Rong et al. 2020). This paper also joins a growing literature that empirically explores the relationship between different factors (e.g., climate and nonpharmaceutical interventions) and the spread of COVID-19 (Fang, Wang, and Yang 2020; S. Chen, Prettner, et al. 2020; Qiu, Chen, and Shi 2020; Pan et al. 2020). Until now, few empirical studies have explored the causal impact of such factors on COVID-19 spread. This paper also contributes to the literature that empirically examines the impact of information disclosure on public health outcomes (Jin and Leslie 2003; Ho, Ashwood, and Handan-Nader 2019; Jin and Leslie 2019). Finally, our paper proposes a novel instrumental variable to cope with the endogeneity of diagnostic confirmation efficiency, which may be useful for exploring other socioeconomic consequences of early public health interventions.

2 Background

COVID-19 was first reported in Wuhan, the capital city of Hubei Province, China, in December 2019 (Wang et al. 2020). China's public health response to COVID-19 was significantly better than its response to severe acute respiratory syndrome (SARS), thanks to lessons learned during that crisis (Wilder-Smith, Chiew, and Lee 2020). Researchers from China obtained and released the genetic sequence of the virus that causes COVID-19 in early January (Wang et al. 2020). Nevertheless, early diagnostic confirmation of COVID-19 infections was initially undertaken very cautiously due to limited knowledge of the virus.

The Diagnosis and Treatment Protocol for Novel Coronavirus Pneumonia (Trial Version) was first released on January 16, 2020.[17] The "novel coronavirus pneumonia," a name given by China in the early stage of the epidemic, was initially named "novel coronavirus (2019-nCoV)" internationally in January 2020 and then officially named "coronavirus disease 2019 (COVID-19)" on February 11, 2020, by the World Health Organization (WHO) (World Health Organization 2020a). China later revised the name to COVID-19 in accordance with the WHO.

According to the official guidance, in addition to epidemiological history and clinical manifestations, confirming an infected case required testing that a high degree of homology existed between the genetic sequence of a viral specimen collected from a patient and the genetic sequences of previously identified COVID-19 samples. This strict criterion complicated and slowed the diagnostic confirmation process. The official guidance was revised on January 18, which updated the criteria for confirming infected cases.[18]

The updated, less-stringent criteria indicated that a positive result for COVID-19

[17] 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.

[18] 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.

nucleic acid from fluorescent RT-PCR could serve to confirm an infected case instead of the established method of determining high homology between the viral gene sequence of a specimen from a diagnosed patient and known coronaviruses. To confirm the first case at the provincial level outside Hubei province, the comparison of genetic sequence, conducted by the central health authority, was still required after the local health authorities confirmed a positive result via RT-PCR. However, subsequent confirmations of first cases in other cities within the province did not require the central health authority's verification. Thus, for all subsequent cities in any province where a case of COVID-19 had been previously confirmed, the overall efficiency of diagnostic confirmation should have improved after January 18, due to the introduction of the fluorescent RT-PCR kit for diagnostic confirmation.

3 Data Sources, Variables, and Summary Statistics

To construct the outcome variable, we rely on two data sources. The first is the China Data Lab (Lab 2020), which provides the cumulative number of confirmed cases (infections and deaths) of COVID-19 in each city from January 15, 2020, to August 2, 2020.[19] According to the data, 297 cities in mainland China had reported at least one confirmed case by August 2, accounting for about 87% of all Chinese cities.[20] The second source is the China City Statistical Yearbook 2019 (National Bureau of Statistics of China 2020), which provides the total number of registered residents in each city by the end of 2018.[21] We include all cities that appear in both datasets and have at least one laboratory-confirmed infected case of COVID-19, except for the city of Wuhan. The final sample consists of 275 cities in the country's 31 provinces and municipalities. We define the prevalence of COVID-19 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 the mortality of COVID-19 as the ratio of cumulative confirmed deaths to the total registered population (in 100 millions) in each city by August 2, 2020. We use the logarithm of the prevalence and mortality of COVID-19 as outcome

[19] The dataset is a part of open resources for COVID-19, available in the Harvard Dataverse (https://dataverse.harvard.edu/dataverse/2019ncov).

[20] The constitution of China provides for three de jure levels of government. Currently, however, there are five practical (de facto) levels, consisting of local government (province, autonomous region, municipality, and special administrative region), prefecture, county, township, and village. In this paper, prefecture-level city and city are interchangeable for simplicity. Cities in this paper also include municipalities such as Beijing, Shanghai, Chongqing, and Tianjin.

[21] These are also the latest data on city-level characteristics available to us.

variables.

For the diagnostic efficiency variable, we construct a novel dataset on the profile of the first laboratory-confirmed cases across all cities in mainland China. To construct this dataset, we manually collected official news and other official reports on diagnostic confirmation and confirmation of recovery or death for the first case in each city. This data collection lasted about three months from early February to early May 2020. The constructed dataset includes general information on the first infected case, such as the infected individual's age, gender, travel history, timing of symptom onset, timing of first visiting a doctor, timing of diagnostic confirmation, and timing of recovery or death. Due to variations in individual responses to illness, the timing of symptom onset may differ from the timing of first visiting a doctor. Therefore, we use the time interval between the date of first visiting a doctor and the date of diagnostic confirmation to the public to measure diagnostic efficiency more precisely. Cities that spend fewer days confirming the first case to the public are more efficient in diagnostic confirmation.

We also construct other city-level variables as follows. First, we construct an indicator of travel time between each city and Wuhan to control for the risk of importing infected cases from the COVID-19 epicenter.[22] Second, we collected city-level data on gross regional product (GRP) per capita, industry structures (including percentage of secondary industry in GRP and percentage of tertiary industry in GRP), 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). These variables capture the risks of disease transmission and the capacity of local health systems. Third, 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.[23] We construct an indicator of healthcare utilization using the number of all discharged patients during the same period in 2019 as the benchmark. These variables, to some degree, can capture the capacity utilization of the health system. Fourth, we collected

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[22] We construct a dataset containing the longitude and latitude information 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.

[23] More details on the number of patients and discharged patients over time can be found in http://www.nhc.gov.cn/wjw/index.shtml.

official news on the launch date for the Level-1 Public Health Incident Alert, the top level of China's public health alert system, for each province or municipality.[24] We construct an indicator 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, or *time interval (first case to public health alert)* for short (**Figure 1**), and use this indicator to capture how responsive local authorities are to COVID-19 after confirming the first case. Different from the *time interval (revised policy to first doctor visit)* that can take both positive or nonpositive values, the *time interval (first case to public health alert)* can only take nonnegative values. More details on the differences can be found in **Figure 1**.

Finally, we collected migration data from two sources. The first is the China Population Census Survey 2015 (National Bureau of Statistics of China 2018).[25] We use the percentage of migrants in the population prior to COVID-19 emergence to capture migration intensity across cities. We also use the percentage of migrants from the COVID-19 epicenter prior to COVID-19 emergence to capture the risk of importing the disease through established migration networks. The second data source is the daily travel intensity (*migration index*) indicators from Baidu Migration, a travel map offered by China's largest search engine, Baidu.[26] The Baidu Migration data are based on real-time location records for every smart phone using the company's mapping app and thus can precisely reflect population movements between and within cities.[27] 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*). These indicators are consistent across cities and across time. The Baidu Migration data have been used in other studies (Fang, Wang, and Yang 2020; Z.-L. Chen, Zhang, et al. 2020).

Table 1 reports summary statistics for the main variables. The average *diagnostic*

[24] Given the large adverse socioeconomic impacts of launching the Level-1 Public Health Incident Alert, local authorities do not adopt the response until the first local case is confirmed. Even after confirming the first local case, some local authorities launch the Level-1 Public Health Incident Alert earlier than other local authorities. In other words, the exact timing of adoption is at local authorities' discretion to some extent.

[25] These are also the latest Population (Mini-) Census data available to us.

[26] Baidu Migration uses Baidu Maps Location Based Service (LBS) Open platform and Baidu Tianyan to calculate and analyze the LBS data and provides a visual presentation to show the trajectory and characteristics of population migration (http://qianxi.baidu.com/).

[27] Baidu has been the dominant search engine in China because all Google search sites have been banned in mainland China since 2010.

efficiency, or the average time to confirm the first case publicly in each city is about 3 days, and the maximum and minimum values are 24 days and 0 days, respectively. Additionally, the average time interval (revised policy to first doctor visit), or the time interval between the date when the local government adopted the updated official guidance (Version 2) on diagnostic confirmation and the date when the first locally diagnosed patient first visited a doctor is 2.5, and the maximum and minimum values are 19 and -18, respectively. **Figures A1–A7** 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 efficiency, the distribution of time interval (revised policy to first doctor visit), and city-level travel intensity (migration indexes) on average over time, respectively.
[Table 1] [Figures A1–A7]

4 Empirical Approach

We estimate regressions of the form

$$Y_c = \alpha_1 + \alpha_2 D_c + X_c \Phi + \mu_c \tag{1}$$

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, and X_c is a vector of city characteristics. The city characteristics include the travel time from city c to the COVID-19 epicenter, the percentage of migrants from the COVID-19 epicenter in the population prior to COVID-19's emergence in city c, GRP per capita, the composition of industry structures, the number of hospital beds per thousand people, the number of public health staff per thousand people, the capacity utilization of health systems, the time interval (first case to public health alert) at the provincial level, and provincial-level fixed effects.[28] μ_c is the error term. The parameter of interest is α_2, which captures the impact of diagnostic efficiency on the prevalence or mortality of COVID-19 locally.

As explained previously, diagnostic efficiency is associated with several factors that affect the outcomes of interest, such as the risk of importing infected cases from the COVID-19 epicenter and the local health authorities' capacity to detect and control the

[28] When controlling for the provincial-level fixed effects, the variables of the time interval (first case to public health alert) and the capacity utilization of health systems are omitted.

disease. For example, the risk of importing infected cases from the COVID-19 epicenter is positively associated with the prevalence or mortality of COVID-19 locally, and if the risk of importing infected cases from the COVID-19 epicenter is also positively associated with the time taken to confirm the first case publicly, omitting this variable will bias the OLS estimate upward. Also possible is that local authorities pursue different strategies to prevent disease transmission (e.g., 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 will bias the OLS estimate downward.

Our empirical strategy takes several steps to overcome these challenges. First, we control for the travel time between each city and the COVID-19 epicenter, which captures the risk of importing infected cases through trade and migration. We also control for the percentage of migrants from the COVID-19 epicenter in the local population to capture the risk of importing COVID-19 through established migration networks. Second, we control for the GRP per capita to capture the local health authorities' capacity to detect and control the disease because cities with higher GRP per capita have more healthcare and other resources. The GRP per capita may also capture the risk of importing infected cases through more intensive economic interactions with other regions. We also control for differences in industry structures to allow for other potential interactions within and across regions that may affect disease transmission locally. Third, we control for the number of hospital beds per thousand people and the number of public health staff per thousand people to capture the city's health system capacity. Fourth, we control for the capacity utilization of health systems at the provincial level to capture the crowdedness of health systems. Fifth, we control for the time interval (first case to public health alert) to capture local authorities' responsiveness in containing disease transmission. Finally, we control for other time-invariant factors at the provincial level through provincial-level fixed effects.

That other unobservable variables (e.g., local authorities' intervention strategies at different stages) may be both correlated with the diagnostic efficiency of confirming the first case and predictive of the outcomes of interest remains a concern. Therefore, we also construct an instrumental variable based on the launch of a national policy on diagnosis to cope with potential endogeneity problems. Infected people who visited a doctor for the first time after January 18, 2020, experienced more efficient diagnostic confirmation on average, largely due to the introduction of improved diagnostic technology, than those who first visited a doctor prior to that date.[29] In addition, following confirmation of the first provincial-level COVID-19 case (which required verification from the central health authority), subsequent confirmations of first cases in other cities within the province did not require central health authority verification. As a result, improvements in both diagnostic technology and the process of information disclosure contributed to improved diagnostic efficiency for local health authorities.

The identifying assumption is that, conditional on the risk of importing the disease from the COVID-19 epicenter, the time interval (revised policy to first doctor visit) is exogenous to any other correlates of the outcomes of interest. This assumption is motivated by the argument that the relative timing of the first infected person's first visit to a doctor depends on quasi-random characteristics when the incubation period lasts for up to 14 days. We further relax this assumption by focusing on cities with smaller windows of relative timing (e.g., 4–7 days) of the first case's first visit to a doctor.

5 Results

In this section we start by showing the estimated impacts of diagnostic efficiency on COVID-19 prevalence and mortality. Then we show the heterogeneous impacts of diagnostic efficiency across cities. We also explore likely underlying mechanisms. Finally, we conduct several robustness checks.

5.1 OLS Estimates

We begin by reporting the OLS estimates for the associations between diagnostic efficiency and prevalence of COVID-19 infections (**Table 2**) and the associations between diagnostic efficiency and COVID-19 mortality (**Table 3**). The unadjusted estimates (i.e., without controlling for other variables) show that, on average, a 1-day reduction in the time to confirm the first infected case publicly is associated with 15% $[(e^{0.14}-1)\cdot 100\%]$ (95% confidence interval [CI]: 11%−21%) and 22% $[(e^{0.20}-$

[29] Physicians would also be more primed to look for COVID-19 thanks to the introduction of improved diagnostic technology.

1) · 100%] (95% CI: 14%–31%) lower prevalence of COVID-19 infections and COVID-19 mortality, respectively.

Columns (2)−(7) in **Tables 2-3** further report the adjusted OLS estimates by adding additional covariates. In the preferred multivariable regression after controlling for provincial-level fixed effects [i.e., column (7)], we find that the association between diagnostic efficiency and COVID-19 prevalence or mortality decreases to 0.00 (95% CI: -0.03–0.04) or 0.03 (95% CI: -0.03–0.09), respectively. As a result, the OLS estimates show insignificant association between diagnostic efficiency and COVID-19 infections or deaths.

As for other variables, the coefficients of the travel time variable for prevalence and mortality of COVID-19 are -0.62 and -0.27, respectively, suggesting that a 1% increase in the travel time from the city to the COVID-19 epicenter is on average associated with 0.62% lower COVID-19 prevalence and 0.27% lower COVID-19 mortality, respectively. We also find that the percentage of migrants from the COVID-19 epicenter in the population is positively associated with COVID-19 prevalence and mortality. Both results suggest that population mobility is an important factor in the prevalence and mortality of COVID-19. Moreover, the positive association between GRP per capita and COVID-19 infections and deaths suggests that more developed cities having more intensive economic interactions with other regions could offset their possibly advantageous capacity in detecting and containing COVID-19. **Tables 2-3** provide more details on the coefficients of other covariates.
[Tables 2-3]

5.2 IV Estimates

The OLS estimate may still be biased when unobserved variables (e.g., various intervention strategies at different stages) are correlated with the time to confirm the first case publicly and predictive of outcomes of interest. To address this concern, we resort to an instrumental variable approach using the time interval (revised policy to first doctor visit).

The first-stage results show that the time interval (revised policy to first doctor visit) is negatively associated with the time taken to confirm the first case publicly. The coefficient of our instrumental variable is -0.51 (95% CI: -0.58 – -0.45) and is statistically significant at the conventional level. Specifically, 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 instrumental variable does not suffer from weak identification problems.

The IV estimate shows that, on average, a 1-day reduction in the time to confirm the first infected case publicly leads to about 9.4% [$(e^{0.09} - 1) \cdot$ 100%] (95% CI: 5%–15%) lower local prevalence of COVID-19 infections and 12.7% $[(e^{0.12} - 1)] \cdot 100\%]$ (95% CI: 4%–22%) lower local COVID-19 mortality, suggesting that the OLS estimate is seriously underestimated. One explanation is that local authorities that delay confirming the presence of COVID-19 will take more rigorous actions (e.g., longer duration of lockdown) to contain disease transmission afterward, and omitting this variable biases the OLS estimate downward. 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 **Tables 2-3**).

5.3 Heterogeneous Effects

Improved efficiency of diagnostic confirmation significantly reduces the prevalence and mortality of COVID-19. In this subsection, we further explore whether the impacts of diagnostic efficiency are heterogeneous across cities. First, we examine whether early detection matters more when there is more time to act (e.g., farther from the COVID-19 epicenter, exposed to less migration)? Second, we examine whether early detection matters more when public health systems are more responsive? Third, we examine whether early detection matters more in the presence of more crowded health systems.

5.3.1 Distance from the COVID-19 epicenter

First, we compare the impact of improved diagnostic efficiency in cities that are closer to the COVID-19 epicenter with that of cities farther from the COVID-19 epicenter based on the travel time variable. Using the IV approach, we find that a 1-day reduction in the time to confirm the first case publicly leads to about 17% (95% CI: 3%–32%) lower local prevalence of COVID-19 infections and 26% (95% CI: 1%–58%) lower local COVID-19 mortality in cities farther away from the COVID-19 epicenter (above the median value of the travel time distribution); in comparison, the same reduction in the time to confirm the first case publicly leads to substantially smaller (6% [95% CI: 2%–11%] and 7% [95% CI: 0%–15%], respectively) reductions in local prevalence and mortality of COVID-19, respectively, in cities closer to the COVID-19 epicenter (**Tables 4-5**).

5.3.2 Migration intensity prior to the pandemic

Second, we compare the impact of improved diagnostic efficiency in cities exposed to more migration (prior to the emergence of COVID-19) with that of cities exposed to less migration. Using the same approach, we find that a 1-day reduction in the time to confirm the first infected case publicly leads to about 19% (95% CI: 5%–35%) lower local prevalence of COVID-19 infections and 25% (95% CI: -2%–58%) lower local COVID-19 mortality in cities with relatively less migration (below the median value of the migration intensity distribution), whereas the same reduction leads to only 5% (95% CI: 1%–11%) and 5% (95% CI: -2%–12%) lower local prevalence and mortality of COVID-19, respectively, in cities with more migration (**Tables 4-5**).

5.3.3 Responsiveness of public health systems

Third, we compare the impact of improved diagnostic efficiency in cities with more responsive public health systems with that of cities with less responsive public health systems. To capture the responsiveness of local public health systems, we use the time interval (first case to public health alert). Using the same empirical approach, we find that a 1-day reduction in the time to confirm the first infected case publicly leads to about 26% (95% CI: 12%–42%) and 25% (95% CI: 3%–52%) lower local prevalence and mortality of COVID-19, respectively, in cities with more responsive public health systems [below the median value of the time interval (first case to public health alert) distribution], whereas the same reduction leads to only 3% (95% CI: -2%–8%) and 6% (95% CI: -2%–15%) lower local prevalence and mortality of COVID-19, respectively, in cities with less responsive public health systems (**Tables 4-5**)

5.3.4 Capacity utilization of health systems

Finally, we compare the impact of improved diagnostic efficiency in cities with higher-capacity utilization of health systems with that in cities with lower-capacity utilization of health systems. To capture the capacity utilization of health systems, we use the ratio of the total number of patients from January 2020 to April 2020 to the total number of patients during the same period in 2019. Using the same empirical approach, we find that a 1-day reduction in the time to confirm the first infected case publicly leads to about 13% (95% CI: 3%–23%) lower prevalence of COVID-19 and 20% (95% CI: 4%–38%) lower mortality of COVID-19 in cities with higher-capacity utilization of health systems (above the median value of the capacity utilization of health systems distribution), whereas the same reduction leads to 9% (95% CI: 3%–15%) and 11% (95% CI: 0%–22%) lower local prevalence and mortality in cities with lower-capacity utilization of health systems (**Tables 4-5**).

In sum, we find significant heterogeneous impact of improved diagnostic efficiency across cities. Specifically, the impact is more pronounced in cities that are farther from the COVID-19 epicenter (17% and 26% for prevalence and mortality of COVID-19, respectively), exposed to relatively less migration prior to disease transmission (19% and 25% for prevalence and mortality of COVID-19, respectively), with relatively more responsive public health systems following confirmation of the first case (26% and 25% for prevalence and mortality of COVID-19, respectively), and with relatively higher capacity utilization of health systems (13% and 20% for prevalence and mortality of COVID-19, respectively). Therefore, these findings suggest that early detection matters more when there is more time to act, when public health systems are more responsive, and when public health systems are more crowded. See more details in **Tables 4-5**.
[Tables 4-5]

5.4 Potential Mechanisms

In this subsection, we further explore likely underlying mechanisms through which improved diagnostic efficiency reduces COVID-19 infections and deaths.

5.4.1 Social distancing

The heterogeneous impacts across cities suggest that reduced travel propensity, or social distancing, may be a possible mechanism through which improved diagnostic efficiency reduces COVID-19 infections and deaths. To further confirm the social distancing mechanism, we study the causal impact of confirming the first case publicly on travel intensity within and between cities in a difference-in-differences framework. We use high-frequency daily data on intra-city travel intensity, travel intensity to other cities, and travel intensity from other cities between January 1, 2020, and March 15, 2020, from the Baidu Migration data, combined with the exact date of diagnostic confirmation for the first infected case locally. The model specification is as follows:

$$\boldsymbol{y_{ct} = \alpha' I_c + \beta' I_t + \gamma\, I_{c,t \geq t_{first\ case}} + \varepsilon_{ct}} \qquad (2)$$

where $\boldsymbol{y_{ct}}$ is the travel intensity indicator (*within-city migration index*, *out-migration index*, or *in-migration index*) in city $\boldsymbol{c}$ on day $\boldsymbol{t}$, $\boldsymbol{I_c}$ is the vector of city fixed effects, $\boldsymbol{I_t}$ is the vector of time fixed effects, and $\boldsymbol{I_{c,t \geq t_{first\ case}}}$ is an indicator for an observation after confirming the first case publicly in city $\boldsymbol{c}$. The error term is $\boldsymbol{\varepsilon_{ct}}$, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are vectors of coefficients to be estimated, and $\boldsymbol{\gamma}$ is the coefficient of interest.[30] We use the estimator proposed by de Chaisemartin and D'Haultfoeuille (2020), which accounts for the heterogeneous impacts across cities and over time, to estimate the causal impact.

Both intra-city and inter-city travel intensity decreased dramatically after confirming the first case publicly (**Figure 2**). For example, using travel intensity indicators during the same period in 2019 as the benchmark, we find that publicly confirming the first (symptomatic) infected case led to 13%, 28%, and 37% reductions on average in intra-city travel intensity, travel intensity to other cities, and travel intensity from other cities, respectively, 3 days after confirmation. These findings suggest that travel propensity is very responsive to the diagnostic confirmation of the first case locally. We do not find similar patterns using travel intensity indicators in 2019 in a placebo analysis (**Figure A8**). These findings suggest that social distancing, induced by confirming the first infected case publicly at an earlier point in time, is a possible mechanism through which improved diagnostic efficiency contains disease transmission.
[Figure 2] [Figure A8]

5.4.2 Avoiding overstressed health systems

Social distancing alone cannot explain that the impact of diagnostic efficiency is more

[30] Assuming that trends in the outcome would have been similar in cities affected by the diagnostic confirmation of the first case to trends in unaffected cities had the diagnostic confirmation of the first case not occurred, the estimate $\hat{\gamma}$ captures the effect of confirming the first case publicly.

pronounced in reducing deaths (12.7%) than infections (9.4%). As such, the impact of diagnostic efficiency on deaths not only comes from fewer COVID-19 infections, but also from other possible pathways. One important and plausible pathway is a less overstressed health system, because it can reduce treatment delays, deliver better healthcare service, ensure sufficient healthcare resources (e.g., ICU beds, ventilators, etc.), and provide better protection of vulnerable groups (e.g., older population and people with chronic diseases, as they are more likely to die than young and healthy populations), all contributing to a higher survival probability (Armocida et al. 2020; Cavallo, Donoho, and Forman 2020; Woolley 2020; S. Chen, Zhang, et al. 2020; Ji et al. 2020). Indeed, we find that, when health systems tend to be overwhelmed, the impact of diagnostic efficiency 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 efficiency on 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 4-5**). These findings suggest that the impact of diagnostic efficiency on deaths also comes from reducing stress on health systems.[31]
[Tables 4-5]

5.5 Impact of Improved Diagnostic Efficiency over Time

Finally, we explore how the impact of improved diagnostic efficiency evolves over time. One possibility is that the role of diagnostic efficiency will weaken as local authorities take more rigorous measures over time (e.g., city-wide lockdowns) to contain disease transmission. To assess this possibility, we estimate the impact of improved diagnostic efficiency on the daily prevalence and mortality of COVID-19 from January 25 to August 2, 2020. We find that, in general, the impacts of improved diagnostic efficiency on prevalence and mortality of COVID-19 increase over time (**Figures 3-4**), which is consistent with our previous findings that improved diagnostic efficiency is complementary with other mobility-restriction policies in containing disease transmission. All this evidence suggests that diagnostic efficiency leads to persistent differences in the spread of COVID-19 across cities.

[31] An alternative explanation could be that not all infections are detected and that the actual reduction in infections is higher than the one registered. Nevertheless, the fact that all deaths come from detected infections reduces this concern to some extent.

[Figures 3-4]

5.6 Robustness Checks

We conduct several robustness checks. First, we further relax our main assumption by focusing on cities with similar dates of the first case's first visit to a doctor. To conduct the analysis, we choose 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. **Table A1** shows the main results for the impact of diagnostic efficiency on the prevalence of COVID-19 infections. We find that using alternative cutoffs does not reject our central findings. Specifically, using a cutoff of 4 days, we find that the coefficient of interest is 0.12 (95% CI: 0.02–0.23), which is close to that found in the benchmark model (i.e., 0.09 [95% CI: 0.04–0.13]). Following the same approaches, **Table A2** shows the main results for the impact of diagnostic efficiency on COVID-19 mortality. Specifically, using a cutoff of 4 days, we find that the coefficient of interest is 0.05 (95% CI: -0.15–0.25), which is smaller than that found in the benchmark model (i.e., 0.12 [95% CI: 0.04 – 0.20]) and is not statistically significant at the conventional level. The insignificant result suggests a bias-variance trade-off when selecting cut-offs. 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.

Second, 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. We re-estimate the impact by dropping those cities that confirm the first infected case at the provincial level and find that the coefficients of interest are 0.10 (95% CI: 0.03–0.16) and 0.13 (95% CI: 0.02–0.23) for the prevalence and mortality of COVID-19, respectively.

Third, the diagnostic confirmation process for the first infected case inside Hubei province may differ from that outside Hubei province. We re-estimate the impact by dropping all cities in Hubei province and find that the coefficients of interest are 0.10 (95% CI: 0.05–0.16) and 0.13 (95% CI: 0.03–0.23) for the prevalence and mortality of COVID-19, respectively.

Finally, the first infected case may be imported from other regions rather than from the COVID-19 epicenter.[32] We re-estimate the impact by keeping those cities that are known to have imported the first case from the COVID-19 epicenter and find that the coefficients of interest are 0.08 (95% CI: 0.03–0.13) and 0.10 (95% CI: 0.01–0.19) for the prevalence and mortality of COVID-19, respectively.
[Tables A1-A2]

6 Conclusion

To the best of our knowledge, this is the first study to investigate the causal impact of diagnostic efficiency on infectious disease epidemics. We take advantage of a plausible exogenous policy, combined with a novel dataset on the profile of the first infected cases of COVID-19 across 275 Chinese cities during January and February 2020. We show that improved diagnostic efficiency is very effective in containing disease transmission and saving lives: a 1-day reduction in the time taken to confirm the first case publicly leads to 9.4% and 12.7% reductions on average in the prevalence and mortality of COVID-19, respectively, over the ensuing six months. This study also shows that disclosing information earlier is effective in reducing travel propensity and that delaying information disclosure can be costly by making local people less prepared for COVID-19.

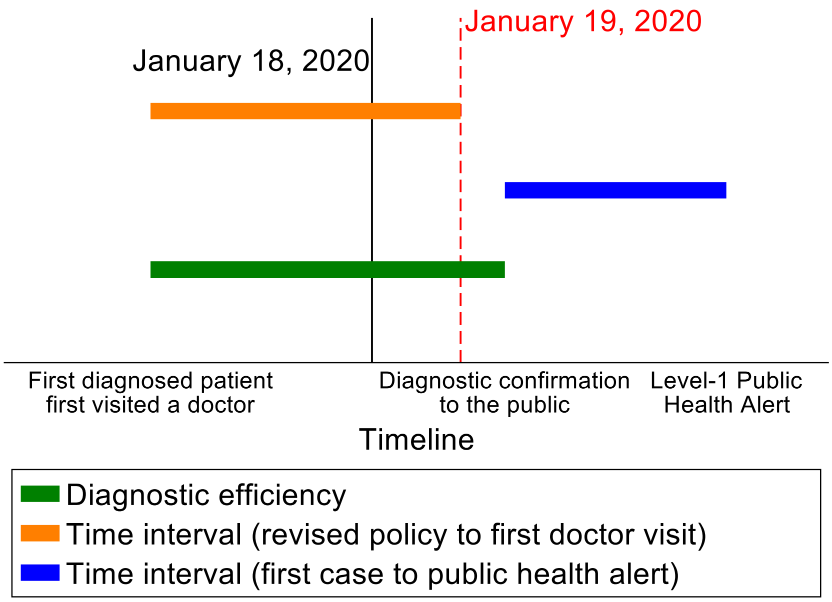
Implementing subsequent epidemic-control measures can boost the effectiveness of diagnostic efficiency in reducing infections and averting deaths. In fact, our findings show that less responsive public health systems would offset the benefits of improved diagnostic efficiency in containing disease transmission and saving lives. These findings shed light on the high prevalence of COVID-19 infections and high death rates in some countries (e.g., the United States) that diagnosed and publicly announced their first case in a timely fashion, but did not respond to the pandemic immediately. Social or cultural differences (e.g., collectivism versus individualism) that affect governmental and societal responses to the pandemic might mediate the effect of information disclosure in different countries. For instance, South Asian countries such as China and

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

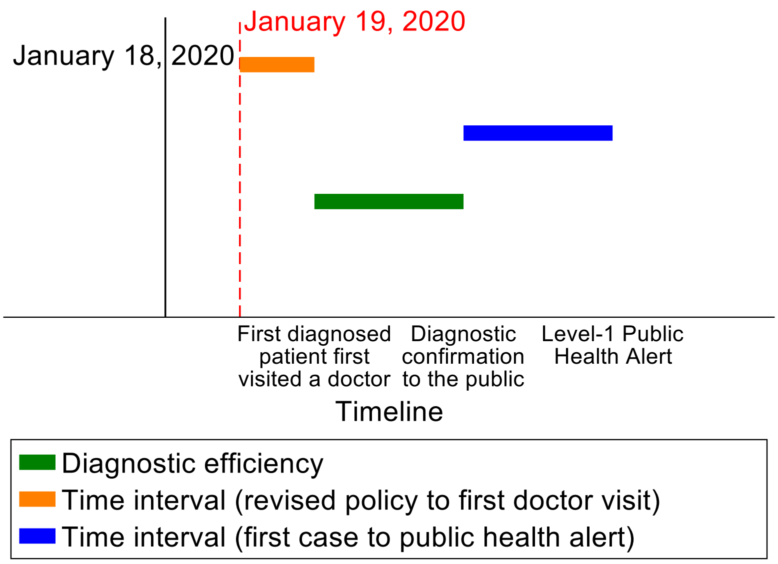
South Korea mandatorily isolated all COVID-19 patients, even the mildly ill, in facilities to prevent intra-family and community infections, while Western countries such as the United States and the United Kingdom recommended mild COVID-19 patients to stay at home and did not strictly enforce those recommendations (S. 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 number of infected cases (e.g., due to inadequate testing, asymptomatic patients, and incomplete information disclosure). This may have particularly been the case during the beginning of the COVID-19 pandemic. However, this concern is reduced to some extent since early February, because at that time, 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; S. Chen, Zhang, et al. 2020). In addition, our finding that the impact of improved diagnostic efficiency persists and even increases slightly over time further reduces this concern. Second, because we cannot distinguish the role of new diagnostic technology adoption from that of improved information disclosure in improving diagnostic efficiency, our findings regarding what determines diagnostic efficiency should be interpreted with some caution. Third, 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 be beyond the scope of this paper.

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



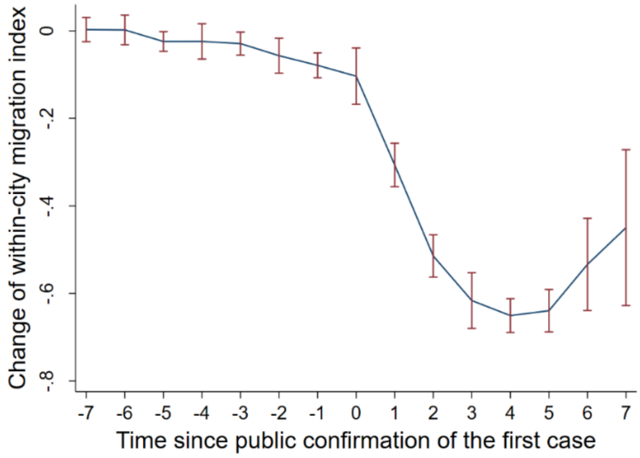
(a)



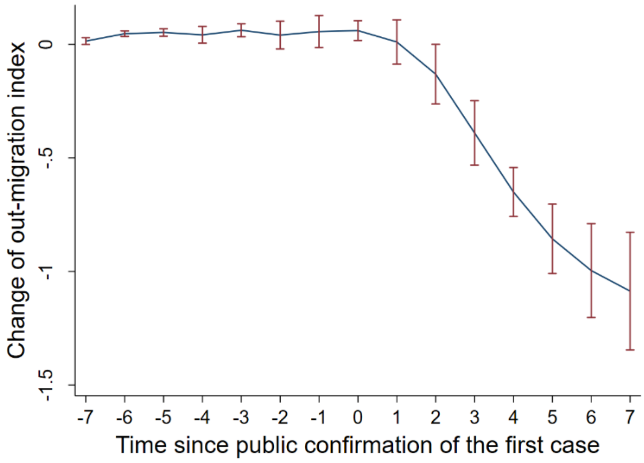
(b)

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

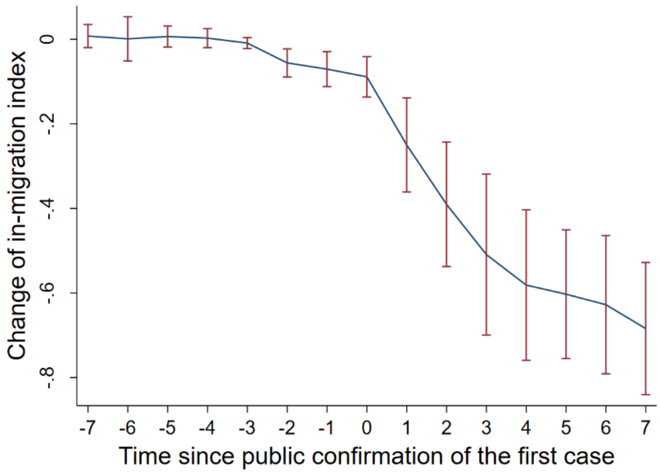
Note: (a) The local government adopted the updated official guidance on diagnostic confirmation of COVID-19 *after* the first diagnosed patient first visited a doctor. (b) The local government adopted the updated official guidance on diagnostic confirmation of COVID-19 *before* the first diagnosed patient 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 efficiency* = 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.



(a)



(b)



(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.

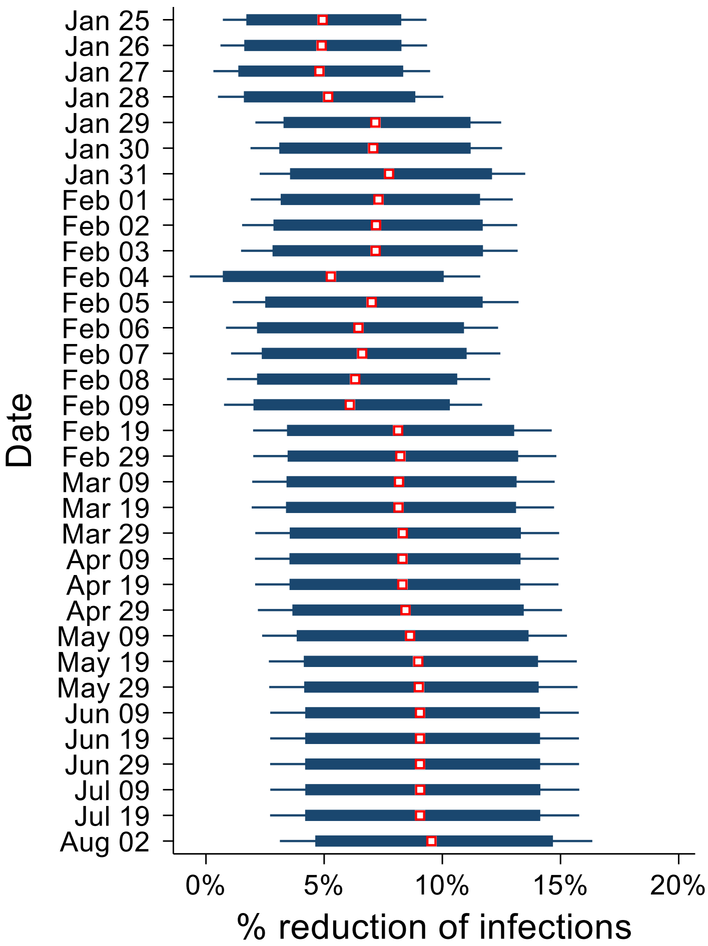


Figure 3 Impact of diagnostic efficiency on the prevalence of COVID-19 infections over time

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

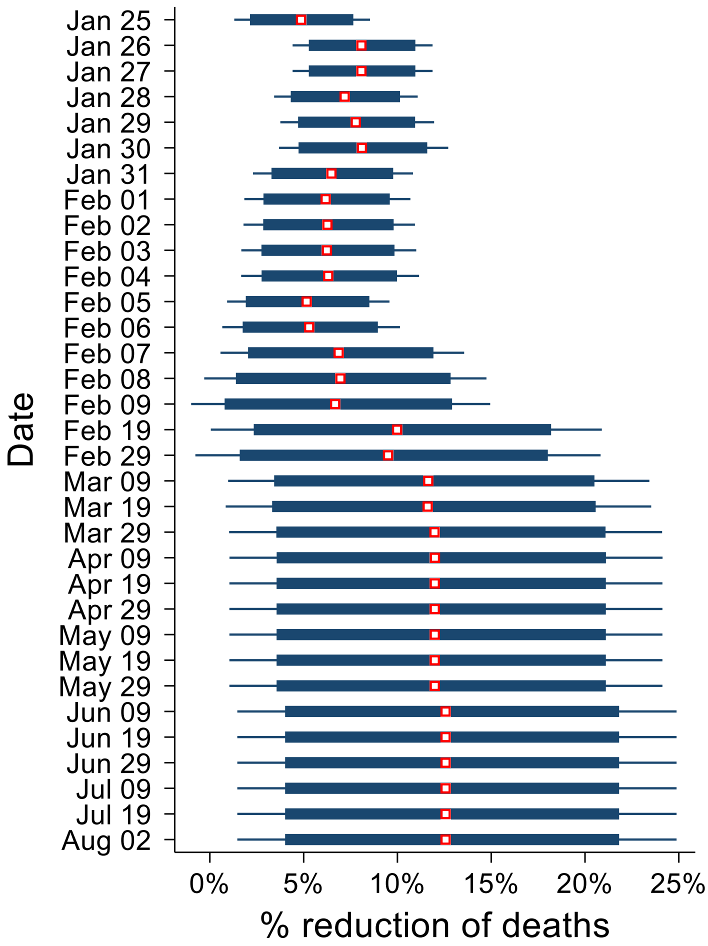


Figure 4 Impact of diagnostic efficiency on COVID-19 mortality over time

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

Table 1 Summary statistics

Variables	N	Mean	Median	Std. Dev.	min	max
Prevalence of COVID-19 (infections per million people)	275	27.30	6.19	102.65	0.41	1255.86
Mortality of COVID-19 (deaths per 100 million people)	275	68.38	0.00	406.30	0.00	5315.32
Diagnostic efficiency (day)	275	3.20	2.00	3.01	0.00	24.00
Time interval (*revised policy to first doctor visit*)	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*)	265	2.56	2.00	0.81	0.00	4.00

Note: *Diagnostic efficiency* = 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 efficiency 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 efficiency (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 efficiency 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. * p<0.1, ** p<0.05, *** p<0.01.

Table 3 Impact of diagnostic efficiency 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 efficiency (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 efficiency 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. * p<0.1, ** p<0.05, *** p<0.01.

Table 4 Heterogeneous impacts of diagnostic efficiency on prevalence of COVID-19 infections

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
Diagnostic efficiency (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)
Logarithm of travel time to the COVID-19 epicenter	-0.72***	-0.23	-0.28	-0.85***	-0.82***	-0.90**	-0.60**	-0.73**
	(0.23)	(0.60)	(0.34)	(0.30)	(0.28)	(0.40)	(0.29)	(0.32)
Percentage of migrants from the COVID-19 epicenter (2015)	-0.08	1.32	1.95**	4.32	1.37	0.64	0.92	5.69**
	(0.87)	(1.60)	(0.98)	(2.92)	(0.85)	(2.79)	(0.93)	(2.62)
Logarithm of GRP per capita (2018)	1.07***	0.60*	0.76**	0.50	1.03***	0.47	0.76***	0.46
	(0.30)	(0.31)	(0.31)	(0.31)	(0.30)	(0.32)	(0.27)	(0.31)
Percentage of secondary industry in GRP (2018)	-0.04	-0.01	-0.02	0.00	-0.04*	-0.01	-0.02	0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Percentage of tertiary industry in GRP (2018)	-0.03	0.01	-0.01	0.02	-0.04	0.01	-0.01	0.02
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Logarithm of hospital beds per thousand people (2018)	-0.10	1.60***	0.30	0.97**	1.07**	0.61	1.42***	0.10
	(0.41)	(0.46)	(0.50)	(0.43)	(0.45)	(0.47)	(0.45)	(0.44)
Logarithm of public health staff per thousand people (2018)	-0.11	-0.88*	0.22	-1.02**	-0.33	-0.27	-0.56	-0.19
	(0.46)	(0.49)	(0.48)	(0.50)	(0.47)	(0.54)	(0.51)	(0.45)
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

Note: This table reports the heterogeneous impacts of diagnostic efficiency on prevalence of COVID-19 infections (the logarithm of COVID-19 prevalence) using the IV approach. Columns 1–2 report the impacts of diagnostic efficiency by distance from the COVID-19 epicenter. Columns 3–4 report the impacts of diagnostic efficiency by migration intensity prior to the pandemic. Columns 5–6 report the impacts of diagnostic efficiency by responsiveness of public health systems. Columns 7–8 report the impacts of diagnostic efficiency by capacity utilization of health systems. Diagnostic efficiency = 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. *** p<.01, ** p<.05, * p<.1.

Table 5 Heterogeneous impacts of diagnostic efficiency on mortality of COVID-19

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
Diagnostic efficiency (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)
Logarithm of travel time to the COVID-19 epicenter	-0.42	-1.06	-0.37	-0.55	-0.34	-0.85	-0.62	-0.08
	(0.42)	(1.07)	(0.50)	(0.58)	(0.48)	(0.65)	(0.55)	(0.51)
Percentage of migrants from the COVID-19 epicenter (2015)	0.18	3.08	2.51*	8.02	1.13	6.08	1.29	6.69
	(1.59)	(2.86)	(1.45)	(5.70)	(1.46)	(4.54)	(1.74)	(4.12)
Logarithm of GRP per capita (2018)	0.74	1.23**	0.89*	1.40**	1.11**	1.20**	1.12**	0.74
	(0.55)	(0.56)	(0.46)	(0.61)	(0.51)	(0.52)	(0.51)	(0.49)
Percentage of secondary industry in GRP (2018)	-0.01	-0.05*	-0.09***	-0.02	-0.07*	-0.03	-0.06**	0.01
	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Percentage of tertiary industry in GRP (2018)	0.03	-0.02	-0.08**	0.02	-0.06	-0.00	-0.02	0.02
	(0.05)	(0.03)	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)
Logarithm of hospital beds per thousand people (2018)	0.03	-0.02	-0.15	0.74	-0.41	0.47	0.28	-0.06
	(0.74)	(0.82)	(0.74)	(0.84)	(0.77)	(0.77)	(0.84)	(0.69)
Logarithm of public health staff per thousand people (2018)	-0.33	-0.46	0.68	-1.53	0.77	-1.16	-0.52	-0.32
	(0.84)	(0.88)	(0.71)	(0.97)	(0.80)	(0.87)	(0.95)	(0.71)
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 efficiency on mortality of COVID-19 (the logarithm of COVID-19 mortality) using the IV approach. Columns 1–2 report the impacts of diagnostic efficiency by distance from the COVID-19 epicenter. Columns 3–4 report the impacts of diagnostic efficiency by migration intensity prior to the pandemic. Columns 5–6 report the impacts of diagnostic efficiency by responsiveness of public health systems. Columns 7–8 report the impacts of diagnostic efficiency by capacity utilization of health systems. Diagnostic efficiency = 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. *** $p<.01$, ** $p<.05$, * $p<.1$.

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Appendix

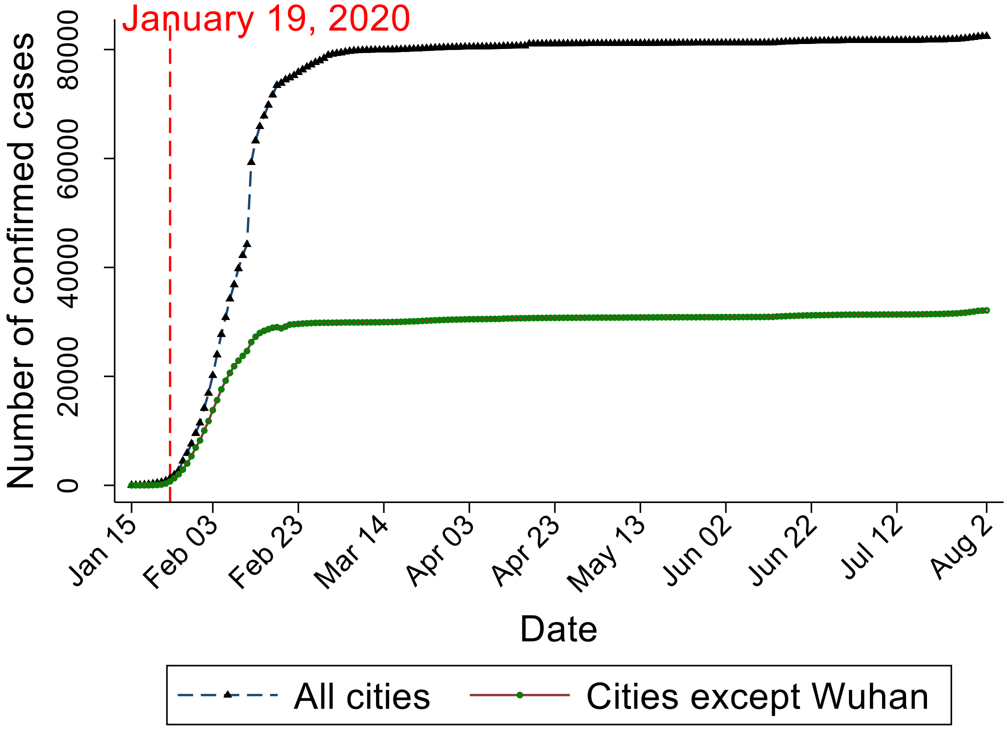


Figure A1 Total confirmed cases of COVID-19 infections over time in China
Note: All dates are in 2020

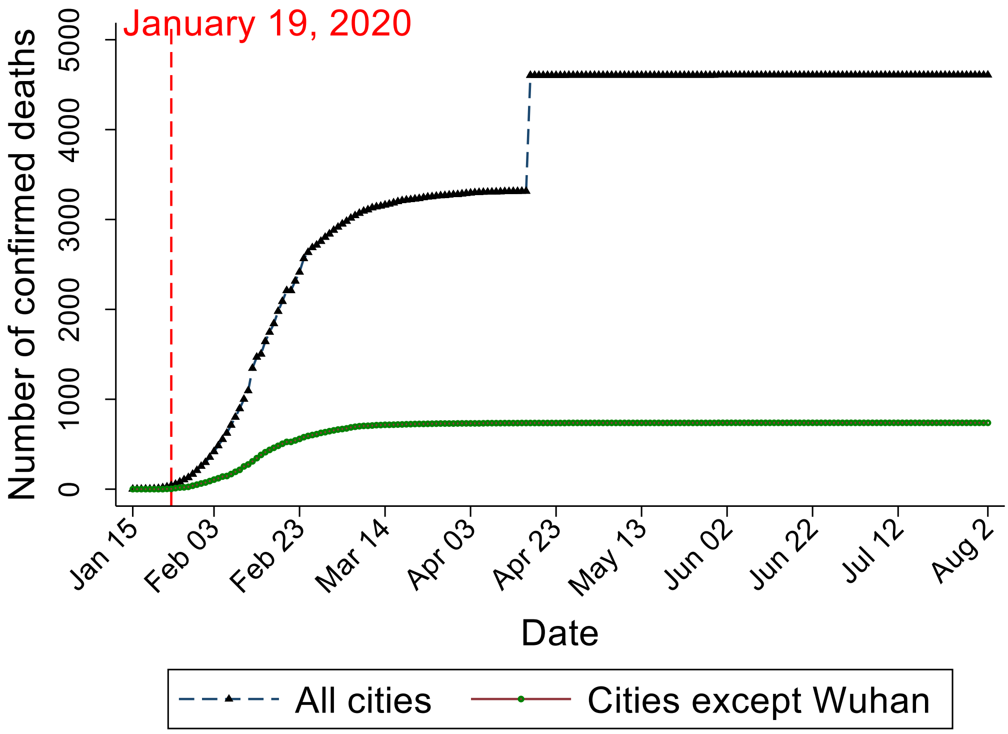


Figure A2 Total confirmed COVID-19 deaths over time in China

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.

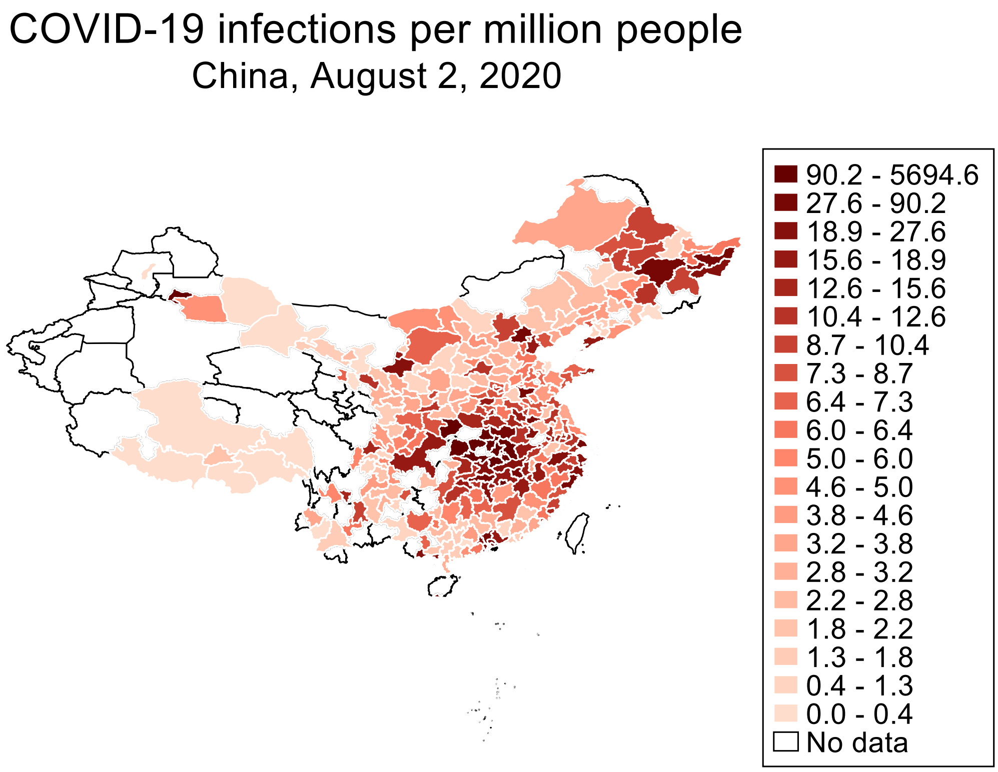


Figure A3 Geographical distribution of the prevalence of COVID-19 infections across cities

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)

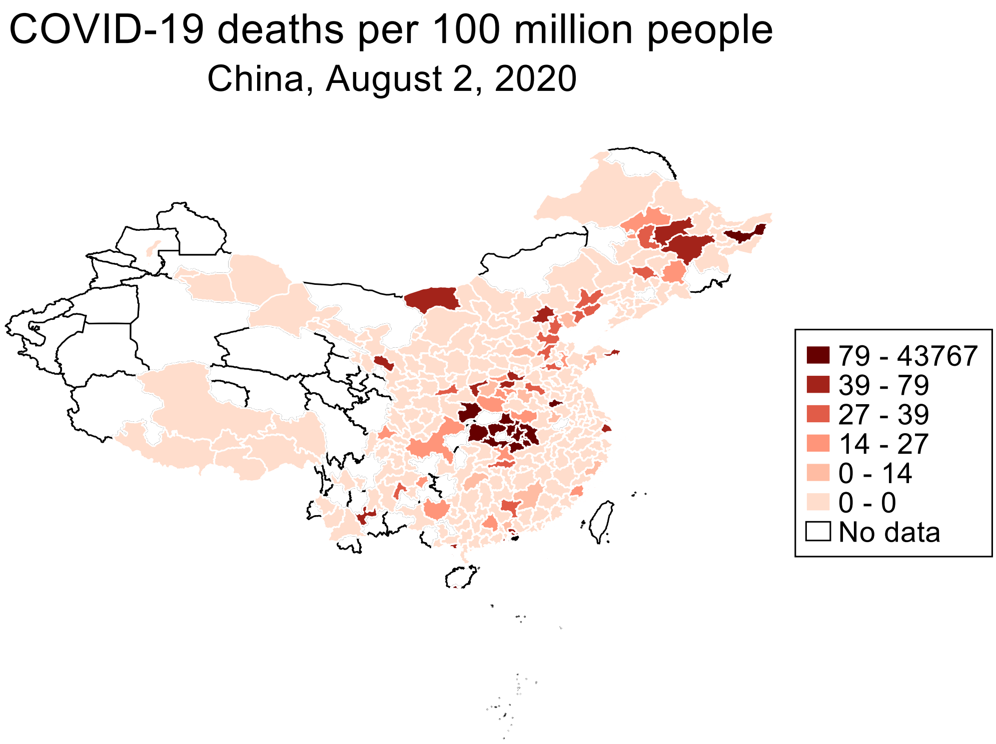


Figure A4 Geographical distribution of COVID-19 mortality across cities
Note: As of August 2, 2020. Source: China Data Lab (http://dataverse.harvard.edu/dataverse/2019ncov); China City Statistical Yearbook 2019 (National Bureau of Statistics of China 2020)

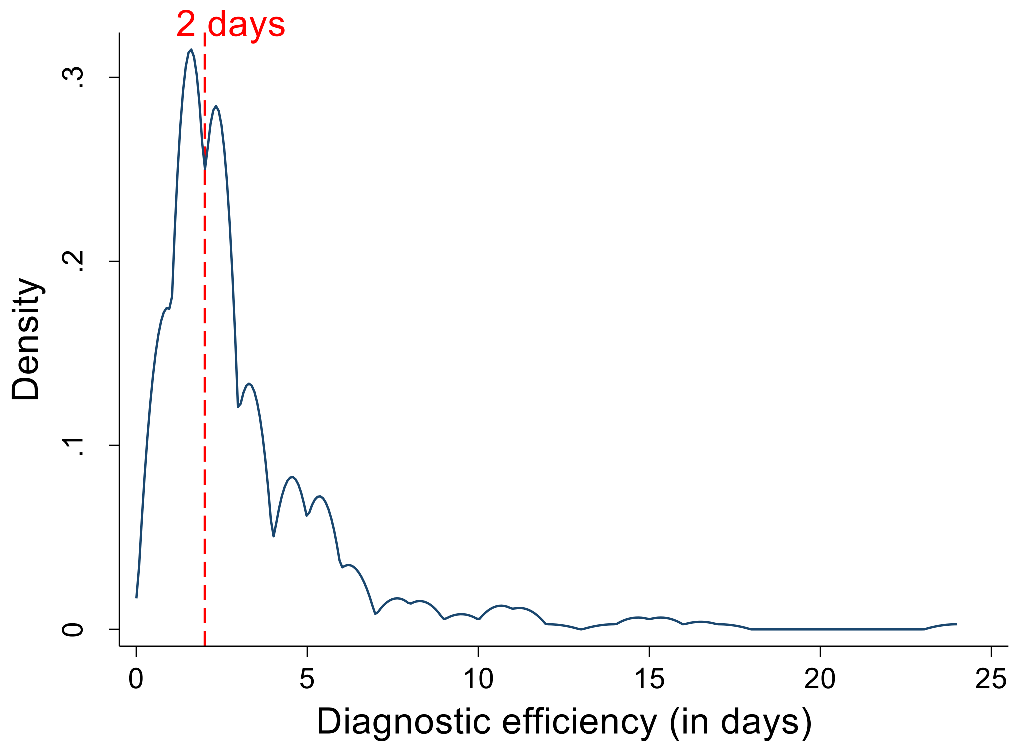


Figure A5 Density of diagnostic efficiency distribution

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

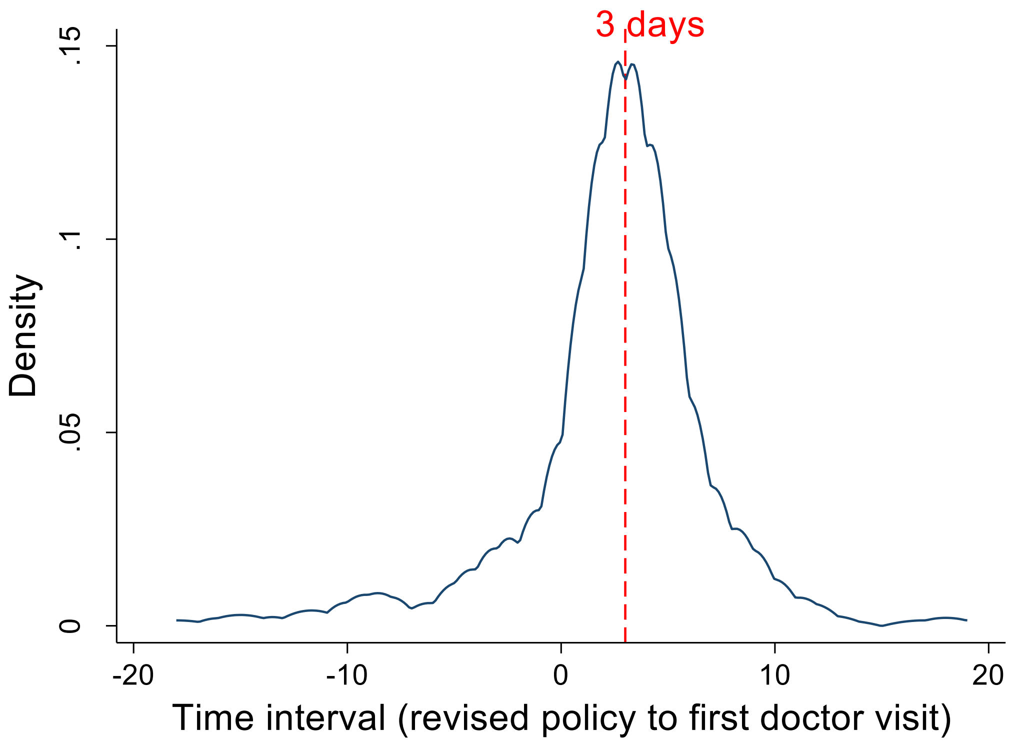


Figure A6 Density of time interval (revised policy to first doctor visit) distribution

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.

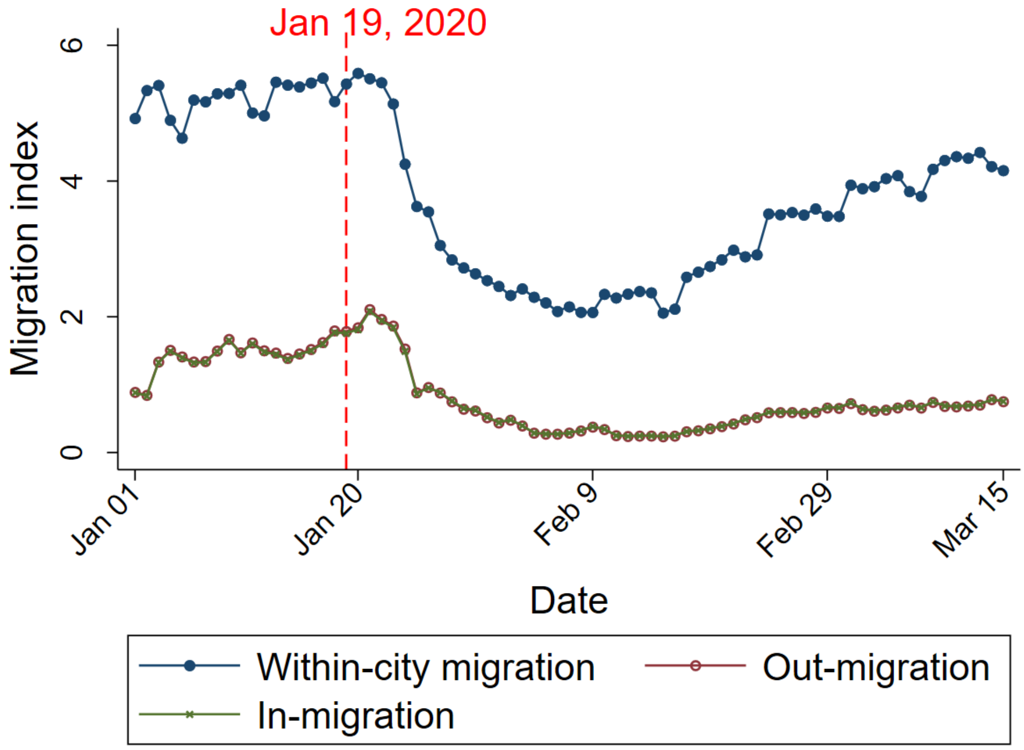
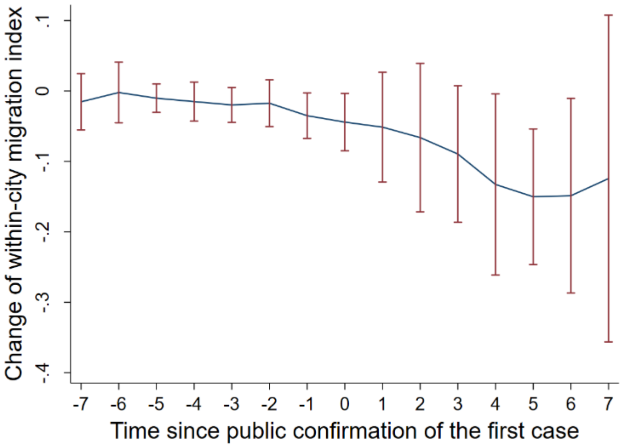
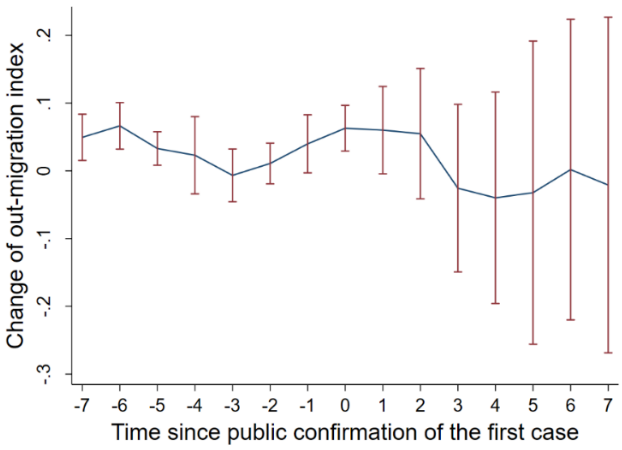


Figure A7 City-level travel intensity (migration indexes) on average from January 01, 2020, to March 15, 2020

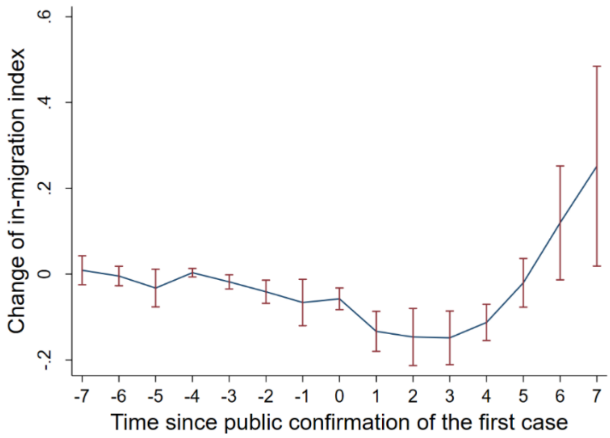
Note: All daily migration indexes comes from Baidu Migration data between January 1, 2020, and March 15, 2020. Within-city migration index = travel intensity within cities. Out-migration index = travel intensity to other cities. In-migration index = travel intensity from other cities. These indicators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



(a)



(b)



(c)

Figure A8. 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.

Table A1 Robustness checks of the impacts of diagnostic efficiency on prevalence of COVID-19 infections

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

Note: This table reports robustness checks of the impacts of diagnostic efficiency on prevalence of COVID-19 infections (the logarithm of COVID-19 prevalence) using the IV approach. Columns 1–4 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 5 reports main results by dropping those cities that confirm the first infected case at the provincial level. Column 6 reports main results by dropping cities of Hubei province. Column 7 reports main results by keeping those cities that are known to have imported the first COVID-19 case. Diagnostic efficiency = 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. *** p<.01, ** p<.05, * p<.1.

Table A2 Robustness checks on the impacts of diagnostic efficiency on COVID-19 mortality

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

Note: This table reports robustness checks of the impacts of diagnostic efficiency on COVID-19 mortality (the logarithm of COVID-19 mortality) using the IV approach. Columns 1–4 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 5 reports main results by dropping those cities that confirm the first infected case at the provincial level. Column 6 reports main results by dropping cities of Hubei province. Column 7 reports main results by keeping those cities that are known to have imported the first COVID-19 case. Diagnostic efficiency = 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. *** p<.01, ** p<.05, * p<.1.