Which Matters More in Coproduction? Political Message, Policy, or Factual Information

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American Review of Public Administration
Online first: https://doi.org/10.1177/02750740231213949

Abstract:

To coproduce better policy outcomes, governments and citizens need to work together. However, information asymmetry between the two parties influences the coproduction adversely. Nowadays, the multiplicity of information and its potential incongruence adds to information asymmetry and makes the impact of information on coproduction trickier than ever. This study examines the effects of political message, policy, and factual information on citizens' coproduction activities. Analyzing the effects of federal and state leaders' tweets, New York City's COVID-19 policies, reported COVID-19 cases and deaths, and the city's visits and public transportation ridership, the findings show that politicians' message, congruent or not, did not influence citizens' coproduction activities as measured by visits and public transit ridership. Policy implementation information improved coproduction, and the perceptions of factual information contributed to intended coproduction.

Keywords: coproduction, policy communication, health communication, information congruence, information credibility, traffic

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To ensure the effective provision of public goods and services, governments and citizens need to work together. The COVID-19 pandemic is a recent case in point: governments alone cannot win the battle against the coronavirus without citizen's coproduction (Chen & Liu, 2020; Li, 2020b) of social distancing, masking, or vaccination. However, citizens are at times reluctant to coproduce public goods and services with governments. Availability, accessibility, and credibility of information are increasingly important factors that potentially either encourage or discourage coproduction (Li, 2021). This Covid pandemic and other major crises have further highlighted the critical need for effective information dissemination and the enormous gap in translating information into coproduction during crises (Garnett & Kouzmin, 2007).

Nowadays, information availability may no longer be an issue, but we argue that the translation of valid information into residents' coproduction faces even more challenges than before: increased distrust of governments in this politically polarizing environment, information asymmetry, misinformation, incongruent messages, and algorithm-enabled group dynamics that self-reinforce social or cognitive preferences for certain types of information. With the rise of the social media age, the traditional ways that residents receive information from authorities such as governments and press organizations are under attack by influential content generated through various social media sites. As Hall (2021, p. 822) pointed out, "Social media, in its nascency, removed barriers to entry into the informal policy agenda." If a government's external communication performance with the public was an issue before (Pandey & Garnett, 2006), the challenge to cut through an increasingly noisy information sphere and communicate policy directions effectively to residents is significantly harder in this social media age.

Adding to the challenge of this multiplicity of information sources are incongruent opinions that are now magnified by social media outlets. For example, if a governor's message was to stay at home to prevent the COVID-19 on a particular day, but a president disagreed and sent an opposite message (e.g., re-opening), then the incongruent messages between leaders send conflicting instructions that are impossible for an individual to follow simultaneously (Acemoglu, 2020; Fukuyama, 2020). In addition, much excellent research on information communication during crises focuses on organizations, for example, cross-sector emergency information networks (Wukich et al., 2019), organizations responsible for protecting citizens (Comfort, 2007), and interagency (Kapucu, 2006). As a result, the impact of information on citizen behaviors during crises is understudied. Our research extends crisis communication to coproduction by citizens as a whole.

Specifically, this study explores both the varying impacts political message, policy and factual information and their incongruence on citizen coproduction behaviors. A comprehensive dataset on citizens' visits and transit activities was obtained to capture the extent to which citizens were co-delivering closing or opening policies by staying at home or not. The three nodes mentioned above recognize three aspects (public administration, public policy, and public health) that Holzer and Newbold (2020) proposed to respond to the COVID-19 pandemic. From an informational perspective, their call for action requires public administrators' messages, policy implementation information, and health-related facts. Although information from private parties may influence citizen co-production, this study focused on public organizations and leaders, which are critical to fighting the coronavirus (Gollust et al., 2020; Hatcher, 2020). The gap that this research aims to address is the heterogeneous effects of different types of public information that were communicated to citizens in order to more effectively persuade citizens to coproduce public service outcomes in times of crises and message incongruence. . Therefore, the study asks how different types of information influence citizens' coproduction activities to shed light on the relationship between information and coproduction and to understand how to inform the public more effectively in the future. This study's main goal is to provide an overview of political messages, policy, and factual information and their effects on citizens' coproduction.

From the start, we shall note that this study focused on the citizens' collective responses to the pandemic and examined the overall effects of three types of information on citizen coproduction at an aggregated city level (New York City). Our study period includes all critical steps in pandemic control and economic recovery between Feb 29, 2020 (the start of the covid outbreak in New York City (NYC)) to September 30, 2020 (well into Phase #4, the last phase of reopening). We posit that information plays an important role in varying effectiveness and survival of policy outcomes that coproduction aims to achieve. In light of the increasingly polarized policy sphere and noisy information sphere, impacts of information multiplicity and incongruence will be a prominent factor in understanding political frictions in coproduction.

The rest of the paper proceeds as follows. After reviewing the literature on coproduction, information asymmetry, communication, and congruence, we then present the data sources and coding schemes used for the analysis. Finally, we show the findings, offer explanations, and discuss the implications.

Literature Review and Research Context

Information Asymmetry and Coproduction

Coproduction, essential to the provision of public services and goods (Ostrom, 1996; Parks et al., 1981), is often defined as the critical mix of activities that public organizations and citizens individually or collectively engage to provide public goods and services that result in positive policy outcomes and individual behavioral changes (Brudney, 2020; Brudney & England, 1983; Li, 2020a). Citizens are not only consumers but also coproducers (Parks et al., 1981; Whitaker, 1980), with some scholars arguing that citizens individually or collectively can co-create values or co-govern with governments (Amorim et al., 2020; Cheng, 2019). One enabling factor is symmetric information sharing between citizens and governments (Brandsen & Honingh, 2016; Brudney & England, 1983; Ferris, 1984; Nabatchi, 2010; Whitaker, 1980). However, previous studies on coproduction overlook that information is often asymmetric (Li, 2020a, 2020b). On the one hand, the unavailability, inaccessibility, and unprocessability of public information worsen the information asymmetry between governments and citizens. On the other hand, even if the information is available, accessible, and easy to process, governments might be unable to communicate information effectively to citizens because of costs associated with customization and personalization of information based on individual information preferences and social demographic characteristics (Li, 2020a). The information asymmetry worsens and influences coproduction more negatively when citizens distrust governments (Li, 2020b, 2021). As Stiglitz (2002) suggested, we need to find ways to reduce information asymmetry in political processes and mitigate its consequences.

Governments now can communicate with the public through various information channels to reduce the degree of information asymmetry. Using information technology, governments can increase their communication effectiveness and responsiveness and thus improve citizen coproduction (Clark et al., 2020; Guan et al., 2021; Wu, Xiao, & Yang, 2021). Particularly, politicians can use social media to better their relationships with citizens if proper information is communicated (Fatema et al., 2020). However, during the pandemic, rumors, conspiracy theories, inaccurate advice, and unsupported suggestions about fighting the virus became overwhelming on social media. The situation of confusing information credibility is worse when the public distrusts governments and the society is politically polarized (Fukuyama, 2020). The public trust in the U.S. government is already relatively low and still declining (Rainie & Perrin, 2019). So, how can governments overcome the deficit of information credibility to promote coproduction in low-trust settings? Some scholars argued that governments can utilize information intermediaries, such as reputable experts and nonprofit organizations, to increase information credibility, rebuild public trust, and improve coproduction of health outcomes (Li, 2020b, 2021; Tsai et al., 2020).

Political Messages, Policies, and Facts

One important question that arises is what kind of information (information types) public organizations should communicate to citizens through different channels in order to reduce information asymmetry and increase information credibility. Different types of information, such as information related to organizational mission and activities, direct requests, organizations' financial and performance-related information, as well as how this information is presented (e.g., framing), can affect citizens in varying ways (Keyworth et al., 2018; Latimber et al., 2005; Li, 2020a).

In this research, we focus on three types of information: political messages, policies, and facts. Incongruent political messages between political leaders, between politicians and public agencies (Duhigg, 2020), and across levels of government (Barber & Dynes, 2021) can cause confusion that leads to non-compliance of policy and impacts coproduction adversely. For example, the U.S. Centers for Disease Control and Prevention (CDC) emphasized clearly that washing hands, masking, social distancing, and even staying at home during certain time periods can curb the spread of the virus, but some political leaders disagreed multiple times (Duhigg, 2020; O'Connor, 2020). Dr. Richard Besser, a former CDC director, worried that the conflicting messages from the then president might confuse and dissuade citizens from coproducing with governments (Duhigg, 2020). "You don't want to go to war with a president," said Dr. Anthony Fauci, Director of the National Institute of Allergy and Infectious Diseases, in an interview (Owermohle, 2020).

In this study, political message congruence(incongruence) means that politicians, who often hold different and even opposing political ideologies, agree(disagree) with each other on a certain issue. In our research setting, it means whether former U.S. President Donald Trump and former NY Governor Andrew Mark Cuomo agreed/disagreed about tightening/lifting COVID-19 restrictions at the same time (day). Studies on the direct impact of politicians' message incongruence on coproduction are limited with most of them focusing on the incongruence between an individual's own belief and information and a politician's opposite belief and information. Some studies suggest that politicians' message incongruence impacts individuals' political attitudes and behaviors (Hopmann, 2012; Lee, 2012; Parsons, 2010). For example, Parsons (2010) found that political disagreement discourages political interests and participation because it depolarizes emotions toward politicians by showing positive emotions toward out-party candidates and negative emotions toward in-party candidates. However, political disagreement does not influence all types of political participation in the same way. According to Lee (2012)'s study, political disagreement reduces position-taking activities that are designed to have individuals taking a set position on a specific issue and increases non-position taking activities. Political disagreement also negatively impacts interpersonal communication and trust (Hopmann, 2012).

The information incongruence between the president and state leaders causes administrative decay and thus further decreases information credibility and deteriorates coproduction. For example, Michigan Governor Gretchen Whitmer issued the “stay-at-home” order to contain the coronavirus. However, the then president criticized and discredited “the woman in Michigan.” Protesters gathered in Lansing, opposing Whitmer’s “stay-at-home” order and ignoring the information about social distancing and wearing masks (Gabriel & Martin, 2020), a demonstration of disengagement in coproduction. It can be expected that an incongruence between Trump’s and Cuomo’s messages about COVID-19 regulations would negatively impact health coproduction activities.

The coproduction might be further negatively impacted when partisanship worsens politicians’ message incongruence. It should be noted that Trump is a Republican and Cuomo a Democrat. A study of political messages’ persuasive effects found that a mismatch of political party identifications increased message rejection depending on expectancies about values traditionally associated with different parties and that citizens especially rejected messages from rival parties when the rival party members evoked unexpected values (Nelson and Garst 2005). Scharmer and Snyder (2021) studied the effects of messages consistency on citizens’ environmental protection attitudes and behavioral intentions and found that messages consistent with an individual's political orientation elicit more pro-environmental attitudes and behavioral intentions; however, the effects of message consistency are limited only to the attitudes and intentions specifically mentioned in the message. To further explore the psychological origin of such bias, Casado-Aranda and colleagues (2020) used the neuroscience method (fMRI) to examine the neural images of political information processing and found that a main partisan bias against political rival parties that stems from higher risk, ambiguity, and disbelief provoked by both positive and negative information about opposite parties. Partisanship could largely influence people's decisions; but regardless of one's political affiliation, the congruence represented a bi-partisan message that should have the same effect on all citizens. Based on the above discussion, we propose:

Hypothesis 1: *Politicians' message incongruence reduces citizens' coproduction activities.*

Second, the impact of policy implementation on citizens' coproduction behavior could be contingent. In this study, policy information is defined as information about policies announced and implemented by governments and is operationalized as the different COVID-19 emergency and re-opening stages announced by the NYC government. Policy implementation information influences a variety of outcomes, such as sustainable development (Mugambwa et al., 2020), environmental outcomes (Dermont, 2019), health policy acceptance and compliance (Allen et al., 2020), and coproduction (Mangai & De Vries, 2019). For example, Allen and colleagues (2020) systematically documented the research on the relationship between policy implementation information and outcomes, and found that policy implementation information positively affects health policy accessibility and compliance. Mangai and De Vries (2019), drawing from cases of rural water agencies and primary health centers from Ghana and Nigeria, show that procedural policy information can make effective and sustainable coproduction.

We posit that policy information matters to coproduction in this case due to a set of factors present in the pandemic. First, the legal framework (Ostrom, 1996) that allowed coproduction (closing and reopening measures that need citizen cooperation) to take place is prominent. The set of closing and reopening policies was direct orders from the then NYS governor and broadcasted everywhere. Therefore, the policy information we studied directly expects a high degree of compliance and coproduction. Second, coproduction behaviors were facilitated by factors like school shutdown and new technologies (such as Zoom) and afforded by the emergency funding from the federal government to residents and companies. Third, "crisis calls for shared responsibilities" between citizens and governments (Steen & Brandsen, 2020, p. 852), but a contagious crisis furthers this notion.

However, policy information might have varying effects on citizens' behaviors. On the one hand, policy may not penetrate citizens' behaviors. As McLaughlin pointed out, a policy cannot always mandate outcomes at the local level. Individual incentives and beliefs are central to local responses (McLaughlin, 1987). Therefore, the influence of policy implementation information on citizens' behavior might be limited. On the other hand, policy could be influential. For example, the Bush Administration used various information technology policies, particularly after the 911, to limit information access that discouraged citizens' democratic participation (Jaeger, 2007). Others have pointed out the contingent nature of coproduction (Steen and Brandsen, 2020). As Dermont (2019) argued, citizens' decisions to support a policy is contingent on the policy itself because the policy information influences the public attitudes and specific reactions. Dermont then examined the effect of policy information on renewable energy usage and found that specific policy information is a crucial factor influencing pro-environmental decisions. For example, when an environmental policy includes shutting down a nuclear power plant, it significantly increases public support (Dermont, 2019). Therefore, we propose:

Hypothesis 2: *Policy information enhances citizens' coproduction activities.*

Third, citizens use other factual information to facilitate their coproduction decisions (for example, Dolnicar et al., 2010). In this study, factual information means the numbers of covid cases and deaths on each day. Factual information's effects on citizens' decisions are contingent on individuals' motivation to change, the context in which decisions are made, and how information is presented all can influence behavioral changes (Kanouse & Jacoby, 1988). For example, simply presenting factual information may not be sufficient to alter individuals' beliefs or behaviors (Fischhoff, 1977). However, Grove and colleagues (1995) found that emphasizing factual information are more effective for intangible services advertisements. Factual information disclosed by government can positively impact people's coproduction during COVID-19 pandemic in China (Wu et al., 2022). When the level of individuals' trust in government is low, how to communicate effectively with the public is important to reduce information asymmetry and increase information credibility that is essential in promoting coproduction (Li, 2020b, 2020a). For example, nonprofit organization can help governments increase information credibility and encourage coproduction (Li, 2021). In addition, different types of factual information influence individuals' policy preferences differently. In a study on immigration policy in the United States, scholars found that presenting facts about immigration's effects on crime, jobs, and taxes increase support for immigration; but presenting facts about immigrant's English acquisition has no impact on individuals' policy preferences (Abascal et al., 2021). Therefore, factual information can be impactful (Borgida & Nisbett, 1977); but its effectiveness depends on the presentation and context of the information.

How does factual information influence citizens' behavior? One explanation is that factual information influences individuals' perceptions of the facts and triggers sequential responses (Fischhoff, 1977; Xu & Li, 2022). Slovic (1987) built a basis for understanding and anticipating public responses to risks and for improving the communication of risk information among citizens, experts, and decision-makers. As argued by Slovic (1987), those who administer and regulate health and safety need to understand how people think about and respond to risk.

Without such understanding, well-intended policy outcomes may not be coproduced. One way to understand how risk perceptions influence decision-making is to understand how risk information including the design, source, and target of message is communicated (Williams & Noyes, 2007). For example, perceived risk increased safe travel behavior and significantly predicted traffic accidents (Lund & Random, 2009). However, studies also showed that facts might not change people's behavior because of confirmation bias (Ma et al., 2019) or social norms (Graham & Roberto, 2016). In the healthcare field, extensive literature has been conducted on how to motivate people to comply with health recommendations by properly framing messages that alter people's perceptions (Rothman & Salovey, 1997; Wilson et al., 1988). A message can be framed in terms of gain (perceptions of positive consequences), loss (perceptions of failing to receive positive consequences), and fear (perceptions of negative consequences) (Wilson et al., 1988). In addition, the literature tends to show that perceptions of gain-framing and loss-framing messages are more effective in influencing low-risk (such as prevention behavior) and high-risk behaviors (such as cancer screening) (Abood et al., 2005; Latimer et al., 2005) while fear-framing messages are more effective in triggering "arousal" or immediate actions (Keyworth et al., 2018) due to individual risk perceptions. For example, death information, given its negative and fear-based perceptions, might be more likely to trigger immediate coproduction (social distancing) than the reported number of cases.

The review of the above literature concludes that factual information contingently influences on citizens' perceptions and thus influences their coproduction activities. Therefore, we propose:

Hypothesis 3: *Factual information facilitates citizens' coproduction activities.*

The Context of New York City (NYC)

We chose NYC as our study site for two main reasons. First, it was the original epicenter of the coronavirus pandemic in the U.S. According to the data provided by the NYC Health Department (2021), the Department classified February 29, 2020 as the start of the COVID-19 outbreak in NYC (i.e., date of the first laboratory-confirmed case). The number of new daily cases exploded from 1 to 6,000 cases a day by the end of March. In the meantime, the NY Governor declared a disaster emergency in the state on March 7, 2020 (NY Government, 2020). By the end of March 2020, the cumulative cases in NYC represented about 62% of the cases in NYS and 25% in the U.S. at the time (CDC, 2020). Since then, NYC has been gradually going through four phases of reopening: Phase One - May 15, Phase Two - May 29, Phase Three - June 12, and Phase Four - June 26. This study covers all stages of closing and reopening from February 29, 2020 (as the start of the COVID-19 outbreak in NYC) to September 30, 2020, (a stable period in the last phase of reopening). This time period allows us to capture the variations of visits and riding activities where politician's message congruence, policy, and factual information changed over different policy stages.

NYC also distinguishes itself in terms of both the quantity and variety of information, which are the independent variables. Comprehensive coverage on the City's Covid cases, deaths and governor's policies by the New York Times, Johns Hopkins's coronavirus dashboard and the CDC is abundant. Both the then President Trump and the then NYS governor were avid users of Twitter. Called a "tweeting town" by Twitter's founder Jack Dorsey, NYC was found to be one of the top cities in the world in terms of active Twitter users (Kaufman, 2012). Twitter data are widely used to research message congruence in health and crisis communication studies. For example, Wang and colleagues (2021) documented the Twitter communications between government agencies and stakeholders during the early stages of COVID-19 and found message incongruence of masking, risk assessment of coronavirus, and stay-at-home orders. At any given time, residents could be at the receiving end of multiple streams of information heightened by the pandemic: congruent/incongruent information from politicians (tweets from the then President/Republican and the then Governor/Democrat), policy information (governor's closing and reopening directives), and factual public health data that is widely available and deemed more objective than other types of information (i.e., reported cases and deaths). This infusion of information types and sources provides a great opportunity for this research to explore the varying impacts, if any, of diverse information on coproduction.

Data and Methods

To examine how information from politicians, policies, and facts influence citizens' visiting and public transit riding activities in NYC, we collected data from several resources to construct a unique dataset (Table 1). To measure citizens' coproduction behavior, data on visits and transit activities were obtained to capture the extent to which citizens were co-delivering closing or opening policies by staying at home or not. How can visits and transit riding activities be considered as coproduction instead of compliance of COVID-19 regulations? Compliance usually refers to the act of following rules, regulations, and policies set by authorities, without necessarily contributing to the implementation process. Compliance can be enforced through legal or administrative measures, such as fines, penalties, or sanctions (Liu et al., 2015). Classic examples are tax compliance (Andreoni et al., 1998) or information security compliance (Bulgurcu et al., 2010). In addition, compliance focuses on realizing private benefits. On the other hand, coproduction refers to a collaborative approach in which service users (consumer coproducers) and providers (regular producers) work together to deliver public services

(Brudney & England, 1983; Li, 2020a; Ostrom, 1996). Coproduction recognizes that service users are not just passive recipients but active contributors to the service delivery process by voluntarily changing their behaviors. In short, policy compliance can be regulatory and mandatory (e.g., tax compliance) and thus does not necessarily require voluntary participation. In our case, citizens coproduce public health outcome by voluntarily reducing visits and public transit riding activities (e.g., staying at home) and realize both private benefits (their own health) and public benefits (public health). Therefore, we consider that visits and riding activities are coproduction activities.

To capture the visits away from home, a comprehensive dataset (Table 1) that contains aggregated visits to about 30,000 points of interest (POIs) in NYC was obtained from SafeGraph (SafeGraph, n.d.). The anonymized location data, collected from mobile devices, is available on a daily basis from March 1, 2020, to September 30, 2020. To provide a robust understanding of citizens' coproduction behavior in NYC, we also collected the daily ridership data from the Metropolitan Transportation Authority (MTA) (MTA, 2021), which includes Access-A-Ride, bridges and tunnels, buses, and subways. Access-a-ride is used to facilitate disadvantaged people; people who live in the suburbs have to commute through bridges and tunnels; and city residents are more likely to use buses and subways. These activity indicators are the dependent variables that we believe capture most citizens' travel activities and represent different elasticities of coproduction activities. Furthermore, this is probably closest to a preliminary study of how information affects different types of residents as different transportation modes are preferred by various groups residents. For instance, residents using bridges and tunnels (arguably consisting of a higher percentage of suburban residents using private cars) are most sensitive to the initial emergency declaration as well as to reopening policies. It should also be noted that working from home citizens would not be affected during the pre-pandemic period and that working from home citizens were captured during the after-pandemic period.

Then, to measure information congruence between politicians, we collected both former U.S. President Donald Trump and former NY Governor Andrew Mark Cuomo's tweets during the same period and independently coded them to measure the degree of federal and state leaders' message congruence. We used rich tweets data to be a proxy for message congruence over a critical period during the COVID-19 pandemic. If multiple COVID-19-related tweets were published on the same day, we first excluded the informational tweets with no clearly identifiable attitudes, then prioritized the ones that showed an attitude, particularly direct communication between Trump and Cuomo. For example, on August 18, 2020, Trump retweeted, "RT @AndrewHClark: Cuomo mismanaged New York's coronavirus response. Tens of thousands in nursing homes unnecessarily died, and his arrogance…"; and Cuomo tweeted, "Advice to the President: 1) When you are in a hole stop digging. The virus is real and spreading. Do your job on COVID. 2) Stop lying. You cannot play Americans for fools. The truth is defeating you." We then coded "1" for the day to represent information incongruence. If no virus information was tweeted, then the first tweet of the day was selected and coded. For instance, on August 16, 2020, Trump did not tweet anything on COVID-19, therefore we selected the first tweet, "8/16/20 RT @bennyjohnson: What if people talked like @JOEBIDEN? Awkward... https://t.co/POpBPnRZSS" and coded it as "0", representing unknown or irrelevant information.

We then coded Trump and Cuomo's tweets by using the following methods: if Trump or Cuomo's tweets mentioned "re-opening" or anything about relaxing the COVID-19 regulation, they were coded as "-1"; if they mentioned nothing on COVID-19 or their attitudes were unknown, then they were coded “0”; and if they mentioned prevention messages, such as “testing, closing business, quarantine, social distancing, and masking”, then “1”.

After that, we used two different strategies to code politicians’ information congruence. We first created the variable “Information Congruence 1” to measure the information congruence between Trump and Cuomo: “-1” represents that Trump agreed with Cuomo and their messages are congruent, “0” represents an unknown condition in which either party or both parties did not disclose their daily COVID-19 attitudes, and “1” represents incongruent information (e.g., Trump criticized Cuomo or vice versa; or Trump wanted to re-open and Cuomo disagreed). However, information congruence could mean different directions. For example, congruence on re-opening is the opposite of congruence on prevention. Therefore, we constructed “Information Congruence 2” to be an alternative measurement of information congruence: if both Trump and Cuomo agreed on re-opening, the condition was coded as “-3”; if one agreed to re-open and the other’s preferences were unknown, then “-2”; if one agreed to re-open and the other disagreed, then “-1”; if both preferences were unknown, then “0”; if one agreed to use COVID-19 preventions and the other disagreed, then “1”; if one agreed to use preventions and the other’s preferences were unknown, then “2”; and if both agreed to use preventions, then “3”. This categorical variable captures the degree of information congruence on prevention from the lowest (-3) to the highest (3).

To measure policy information, we included the implementation of various COVID-19 policy stages in NYC. We coded the pre-emergency stage as 0 and set it as the reference. Then, we coded the state emergency stage, non-essential close stage, and four stages of reopening as 1, 2, 3, 4, 5, and 6, respectively. In addition, factual information was measured by confirmed cases and the number of deaths, both collected from the NYC government. We did not include the number of people hospitalized because the data was pooled, unclear, and noisy.

We then performed a series of multiple variable regressions (Ordinary Least Squares) to test the effects of various types of information on citizens' coproduction behavior measured by visits and public transportation ridership. The next section presents our findings.

Results

Descriptive Statistics

Table 1 describes the main variables. To measure the coproduction behavior more accurately, we excluded the estimated visits by essential workers to gauge voluntarily-reduced visits and public transportation ridership. Specifically, we first used the smallest numbers of visits and ridership on a work day between March 20th, 2020 (the day NYC started non-essential closing) and May 14th, 2020 (the day before NYC's first phase re-opening) to approximately measure the essential workers' visits. We then subtracted the estimated numbers of essential workers' visits (63,779), ridership of Access-A-Ride (4,202), buses (35,2000), bridges and tunnels (254,735), and subways (254,792) from the original numbers and gauged the voluntary travel behavior. The estimated voluntary citywide total visits ranged from 0 to 440,752 with an average of 142,155.60 (SD=101,646.50). In NYC, on an average day during the research period, the numbers of Access-A-Ride service, buses, bridges and tunnels, and subways ridership are 10,049 (SD=6,364.06), 637,922.90 (SD=389,002.40), 463,747.10 (SD=213,350.10), and 922,104.70 (SD=966,364.70), respectively.

[Table 1 here]

In terms of politicians' information, as mentioned above, we coded information congruence between Trump and Cuomo in two different forms. As shown in Table 1, information congruence condition was mostly unknown (58.41%), followed by incongruence (28.04%) and congruence (13.55%). When we coded information congruence incrementally from both supporting re-opening to both supporting prevention, the most common congruence condition was one prevention and the other unknown (42.52%), followed by both unknown (20.09%), one re-open and the other disagreed (14.02%), one re-open and the other unknown (11.21%), both unknown (9.35%), both re-open (1.87%), and one prevention and the other disagreed (0.93%).

In terms of policy information, the duration of COVID-19 policy stages in NYC varied in days. During our research period, the most common stage is the fourth phase of re-opening stage (45.33%), followed by the non-essential close stage (26.17%), the first, second and third phases of re-opening stage (6.54% each), the state emergency stage (6.07%), and the pre-emergency stage (2.8%) that serves as the reference in our models. At the same time, on average, NYC had 1,130.95 (SD=1,519.78) confirmed COVID-19 cases and 88.26 (SD=154.18) deaths daily (measuring factual information). As the standard deviation values show, the variations in NYC's daily confirmed COVID-19 cases and deaths are quite large. It should be noted that there was a three-day reporting lag in the factual information published by the NYC Department of Health (NYC Health, 2021), meaning that the most recent data in today's update are from three days before. In addition, 150 days of the research period were weekdays (70%) and 64 were weekends and holidays (30%). We controlled the weekdays because people moved less during weekends and holidays during the pandemic.

Regression Results

Table 2 presents the baseline effects of the different types of information on NYC visits and public transportation ridership. We believe that changes in public transit ridership capture the impacts of information congruence better, if any, because passengers cannot maintain social distance as easily as outdoors. As shown in Models 1 – 5, whether politicians' information was congruent did not affect citizens' coproduction behavior at a 0.05 significance level (Hypothesis 1 not confirmed). We offer three explanations of the null effects of politicians' messages on social media. First, it could be the limit of Twitter. The relationships formed via Twitter may not be enough to motivate coproduction because coproduction is "intrinsically relational" (Sorrentino et al., 2018, p. 218). Second, it could be the limit of politicians. Citizens may not take politicians' words seriously and thus the influence of politicians' words in their behavioral changes is very limited. Third, such behavioral change as social distancing resembles the characteristics of "enhanced coproduction" that sits at the top tier of the coproduction scale. According to Sorrentino et al. (2018, p.282), "[e]nhanced coproduction is time-dependent because the services require routinization, i.e. the embedding of new practices at all levels: individual, organizational and system." With numerous daily tweets and shifting incongruence between the two leaders, the politicians' messages may not stay long enough to lead to enhanced coproduction.

Policy information, on the other hand, significantly reduced the number of NYC visits across different policy stages at the 0.01 level (Model 5). For example, compared with the pre-emergency period, citizens significantly ($p<0.01$) reduced visits by 126,632.60 (SD=33,062.89), 296,525.40 (SD=33,125.11), and 294,985.90 (SD=32,216.20) times during the state emergency period, non-essential close period, and the first phase of re-opening, respectively. Citizens also significantly ($p<0.01$) reduced their usage of Access-A-Ride (Model 1), buses (Model 3), and subways (Model 4) across all policy stages. From policy stages 1 to 4, as compared to the pre-stage emergency stage, travels through bridges and tunnels decreased significantly at the 0.01 level; such travels did not significantly decrease at stages 5 and 6 (Model 2). We argue that policy implementation information has a stronger and more direct impact on citizens' coproduction decision-making than politicians' words (Hypothesis 2 confirmed).

Models 1, 2, 3, and 4 also showed that the factual information of COVID-19 deaths significantly decreased the usage of Access-A-Ride, bridges and tunnels, buses, and subways by 18.32 (SD=4.99), 441.54 (SD=116.06), 1,191.70 (SD=303.37), and 3,410.47 (790.23) times, respectively (statistically significant at the 0.01 level). However, Models 1, 3, and 4 showed that the factual information of confirmed COVID-19 cases increased the usage of Access-A-Ride, buses, and subways by 1.56 (SD=0.53), 94.24 (SD=32.24), and 352.96 (SD=83.97) times (significantly at the 0.01 level), though the magnitudes were relatively small as compared with the magnitudes of COVID-19 deaths. One possible explanation for why increased confirmed cases led to more public transit activities is that a small amount of people who were confirmed need to see the doctor by using public transit. Compared to the number of COVID-19 cases, death has a negative framing effect that discouraged visits and ridership. It confirms Hypothesis #3 in that message framing matters to coproduction.

Robustness Checks

We performed a series of robustness checks to validate our baseline results (Figure 1). First, we used an alternative measure of coproduction behavior: citizens voluntarily adjust their travel activities to coproduce COVID-19-related health policy outcomes (Robustness check #1). We used the mean of visits and ridership between March 20th, 2020 (the day NYC started non-essential closing) and May 14th, 2020 (the day before NYC's first phase re-opening), excluding weekends and holidays, to measure the visits and ridership of essential workers. We then subtract the above-calculated means from the original values of visits and ridership in the baseline models to estimate the voluntary coproduction activities (Appendix Table 1).

Second, because politicians could agree but in two opposite directions (prevention vs re-opening), we changed the measurement of politicians' information congruence into an incremental ordinal variable (Information Congruence 2) to capture the direction of congruence (Robustness check #2). We coded politicians' information congruence from both supporting re-opening (-3) to both supporting prevention (3) (Appendix Table 2).

Third, because politicians' information incongruence might influence citizens' travel decisions differently across different policy stages, we then created interaction items between politicians' information incongruence and a dummy variable of policy stages (Robustness check #3 and #4). The dichotomized policy stages (the pre-reopen stage =0 and the reopen stage=1) are necessary to ensure that each stage has a sufficient number of observations. We then tested the effects of the interactions on visits (Appendix Tables 3 and 4). The results showed that if politicians' information congruence was unknown to the public during the re-opening stage, it discouraged coproduction significantly by decreasing the number of total visits by 92,325.80 (Appendix Table 3 Model 5) and the number of bus ridership by 773,523.40 (Appendix Table 4 Model 3). However, the null effects of politicians' information incongruence on travel activities during the re-opening stage further confirmed the baseline findings.

As mentioned before, the base model reports factual information of the COVID-19 cases and deaths with a three-day reporting lag (NYC Health, 2021). However, factual information with shorter lagging periods could influence citizens' behavior because they might gather pieces of factual information even though the information was not reported yet. We therefore tested factual information with one-day (Robustness check #5) and two-day lag (Robustness check #6) (Appendix Tables 5 and 6). The results showed that the increased lagging of factual information shrank the impact of factual information on coproduction. On average, if the death information lagged one day, one more death significantly decreased the numbers of using Access-A-Ride, bridges and tunnels, buses, and subways by 24.55, 530.71, 1,561.04, and 4,451.34, respectively (Appendix Table 5). The corresponding numbers were reduced to 23.34, 515.67, 1,515.96, and 4,247.18 (Appendix Table 6) if death information lagged two days, and further to 18.32, 441.54, 1,191.70, and 3,410.47 (Table 2), if death information lagged three days. One implication might be that citizens collected such information by themselves and adjusted their travel activities accordingly even before the government publicly released death information.

One might also argue that the null effects of politicians' information congruence were not surprising as liberal-leaning NYC, with 76% of its citizens voting for Biden in 2020, would follow the Democratic governor's message. If that was the case, we could expect that Cuomo's tweets would influence people's travel activities while Trump's tweets would not. However, if citizens in general are not interested in politicians' information (Wojcieszak et al., 2021), we could expect that neither Trump's nor Cuomo's information would influence travel activities. To tease out this nuance, we tested the effects of Trump's (Robustness check #7) and Cuomo's tweets (Robustness check #8) on travel behaviors, respectively (Appendix Tables 7 and 8).

[Figure 1 here]

All the robustness checks either fully or significantly partially confirmed the baseline results (Figure 1). Considering all the findings together, we concluded that our baseline results were robust: politicians' information congruence had no effects on coproduction activities as measured by NYC visits and public transit ridership; policy information is most significant in improving coproduction; and COVID-19 deaths' negative framing registers intended coproduction outcome: discouraging public transportation ridership.

Conclusion and Discussion

Information plays a key role in motivating citizens' coproduction. However, how citizens translate information into coproduction remains a challenge (Garnett & Kouzmin, 2007). This research, using tweets from Trump and Cuomo, NYC's COVID-19 policies, COVID-19 cases and deaths, and visits and public transit ridership in NYC, estimated the impact of multiplicity and incongruence of information (politicians' message congruence, policy information, and factual information) on citizens' coproduction behavior. Our results did not show supportive evidence that politicians' information incongruence as communicated via Twitter reduces coproduction. However, policy implementation information is important for inducing coproduction. As a result, we argue that, in a politically polarized society, clearly defined and delivered policy information could be effective in improving coproduction at the individual level. To mitigate the political polarization and improve coproduction, governments can boost information credibility by using intermediates such as recognized experts and independent nonprofit organizations in communicating policies. Credible information can help combat the virus and coproduce a healthy society in the future by reducing information asymmetry and increasing public trust in governments (Li, 2020b, 2021). The effects of factual information about reported COVID-19 cases and deaths are mixed. Yet, the framing of factual information matters: the negative framing of death registers more impact on coproduction than cases.

This study contributes to the literature on the relationship between public information communication and citizens' coproduction behaviors in several ways. First, very few existing public administration studies discussed the issue of information asymmetry between the governments and citizens and how it might affect citizens' coproduction activities (Li, 2020a). This research, recognizing the asymmetric nature of information between governments and citizens, emphasizes the importance of information communication in coproduction. It implies that future studies should treat information asymmetry seriously in researching the relationship between government and citizens, particularly in areas where citizens play a significant role in providing public goods and services, such as coproducing health outcomes during a pandemic.

Second, not all information is considered equally by citizens in their coproduction calculation. Different types of information have varying effects on citizens' coproduction behavior. Most of the existing literature researching how information influences citizens' reaction to governments tends to focus on one single type of information. For example, who announced the policy, even that the information was communicated symbolically, could have varying effects on citizens' coproduction decisions (Riccucci et al., 2016; Van Ryzin et al., 2017). This study goes beyond one type of information and examines three different types of information that are widely visible to the public. We found that policy information impacts citizen coproduction the most, followed by factual information with a proper message framing. It should be noted that although multiple sources of information have varying effects on coproduction, the multiplicity of information sources does not necessarily hamper coproduction and could even be complementary under proper framing. More importantly, it indicates that a study of the effect of information in coproduction could consider and differentiate the source and nature of information itself to better estimate the effects.

Third, this study advances the literature by providing one empirical example about the influences of information incongruence on coproduction. Studies on political communication have suggested significant influences of politicians' messages on citizens' perceptions and behaviors (Bartels, 1993; Hopmann, 2012; Iyengar & Simon, 2000). However, this study finds that politicians' message incongruence does not affect citizens' coproduction behavior. This finding suggests that while political communication can have a significant impact on public perception and attitudes, it may not always translate into changes in behavior. In our case, politicians' incongruence has no significant bearing on the coproduction outcome. However, not talking about a coproduction behavior can signal that coproduction is no longer important, and may be more potent in reducing coproduction than incongruent messages. This highlights the complex nature of the relationship between political messaging and citizen behavior, which warrants further investigation.

The study also has direct practical implications. First, in an increasingly polarized political environment with diverse information sources, the findings of this research suggest that policy information remains crucial to deal with political frictions and cut through the informational busyness that coproduction faces. Therefore, public communication during a public health crisis needs to focus on policy, in particular, policy implementation information. Although our findings suggest that politicians' message incongruence may not directly affect citizens' coproduction, it may create confusion and distrust, which may ultimately undermine coproduction efforts in the long term. Therefore, for individual politicians, delivering clear and transparent messages regarding health policies and measurements during times of crisis, such as the COVID-19 pandemic, is crucial to encouraging citizens' coproduction.

Second, factual information with proper framing is much more effective than neutral factual information. Facts matter but the presentation of facts matters more in coproduction. Our results show that confirmed cases might even encourage people to use public transit during the pandemic. To reduce the spread of virus like COVID-19 and ensure public health, officials and policymakers should focus on communicating more salient information, such as death numbers in this case, with the public. For example, policymakers can use death numbers to effectively increase public awareness of the virus and help reduce the spread of COVID-19.

Third, different sources and natures of information could be complementary with each other in motivating coproduction. Therefore, it could be worthwhile for policymakers and public health officials to strategically design information communication in multiple ways. And, last but not least, incongruence of politicians' information via Twitter may be limited in its effects. The absence of politicians' information, however, may discourage coproduction in some cases.

This study is not without limitations. First, we used the number of visits and public transit ridership to proximately measure the coproduction activities that aim to curb the spread of COVID-19 and fight against the virus. We could measure such coproduction activities more directly by using the number of people wearing masks, keeping social distance, and even quarantining on a daily basis if such data were available and accessible. Future studies should refine the measure of coproduction outcomes.

Second, we did not explore the limits of Twitter communication in this study. The effects of social media communication on changing individual behavior and decisions are smaller than expected. For example, relying on social media to obtain nonprofit information cannot motivate individual charitable giving effectively (Li, 2017; Li & McDougle, 2017). Another study also found that the exposure to partisan and centrist news on political polarization—no matter if it is congenial or crosscutting—did not affect polarization. The authors suggested that the null results accurately portray the reality of limited effects of news in the "real world" (Wojcieszak et al., 2021). Future studies should consider the limitations of social media communication and try alternative information congruence measures.

Third, people (in this case Trump and Cuomo) do not post on twitter every day and not all postings are about specific topics (in this case, COVID). As a result, we expect to see unknown information congruence/incongruence between Trump and Cuomo on some days: at least one political leader's opinion was unknown on 58% of the days under study while both opinions were unknown on 20% of the days. While this is the reality of Twitter, we would like to acknowledge that the unknown category could impose limitation on the significance of our results. In other words, the null effects of message incongruence on coproduction could result from the insufficient variance in the message incongruence variable. Therefore, the results need to be interpreted with cautious.

Fourth, this study did not examine the information's heterogeneous effects on different citizens and the moderating effects of individual characteristics, such as partisanship. In addition to information, factors other than citizens' socio-demographics also affect their coproduction decisions. For example, citizens' political party affiliation (Nelson & Garst, 2005), specific skills or knowledge (Alford, 2002; Levine, 1984), motivation to coproduce (Alford, 2002; Brudney, 1983; Powers & Thompson, 1994; Rosentraub & Sharp, 1981), and information preferences (Li, 2020a, 2020b) all influence their coproduction behavior. Furthermore, this study did not investigate how partisanship shapes the relationship between information and coproduction. This study also did not investigate the roles of motivations and information preferences in the relationship between information commination and citizens' coproduction. It certainly warrants further investigation to explore how different types of information influence different citizens without various motivations and information preferences. It should also be noted that Twitter users do not represent the population. For example, Twitter users tend to be younger and more educated. Future studies should address the limitation by examining the difference between different groups varying in age and education levels. This study provided an overall picture of how different types of public information influenced citizen’s coproduction during the pandemic. Future studies should certainly explore the heterogeneous effects of information on different groups of citizens.

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Table 1: Descriptive Statistics of Selected Variables

Descriptive Statistics	N	Min	Max	Mean / Percent	St. Dev.	Data Sources
Total Visits	214	0	440,752	142,155.60	101,646.50	SafeGraph
Access A Ride	214	0	30,970	10,049.00	6,364.06	MTA
Buses	214	0	2,066,700	637,922.90	389,002.40	
Bridges and Tunnels	214	0	945,408	463,747.10	213,350.10	
Subways	214	0	5,261,153	922,104.70	966,364.70	
Trump Tweets	214					Twitter
Re-open (-1)	42			19.63%		
No Information (0)	148			69.16%		
Prevention (1)	24			11.24%		
Cuomo Tweets	214					
Re-open (-1)	26			12.15%		
No Information (0)	50			23.36%		
Prevention (1)	138			64.49%		
Information Congruence 1	214					
Congruence (-1)	29			13.55%		
Unknown (0)	125			58.41%		
Incongruence (1)	60			28.04%		
Information Congruence 2	214					
Both re-open (-3)	4			1.87%		
One re-open, the other unknown (-2)	24			11.21%		
One re-open, the other disagreed (-1)	30			14.02%		
Both Unknown (0)	43			20.09%		
One Prevention, the other disagreed (1)	2			0.93%		
One Prevention, the other Unknown (2)	91			42.52%		
Both Prevention (3)	20			9.35%		
Policy Stages	214					NY.gov
Reference, Pre-emergency (0)	6			2.8%		
State Emergency (1)	13			6.07%		
Non-essential Close (2)	56			26.17%		
First Phase Re-opening (3)	14			6.54%		
Second Phase Re-opening (4)	14			6.54%		

Third Phase Re-opening (5)	14			6.54%		
Fourth Phase Re-opening (6)	97			45.33%		
NYC Cases (3-day lag)	214	0	6,353	1,130.95	1,519.78	NYC.gov
NYC Deaths (3-day lag)	214	0	598	88.26	154.18	
Weekdays	150			70%		
Weekends and holidays	64			30%		

Note: Numbers of visits and ridership are numbers that exclude the estimated essential workers. The visitors' data was collected from SafeGraph, a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than two devices visited an establishment in a month from a given census block group. The number of points of interest visited in the study period are: 30760 (March), 26777 (April), 27468 (May), 28604 (June), 29157 (July), 29634 (August) and 29861 (September).

Table 2: Baseline Effects of Different Types of Information on Coproduction Activities

	NYC Visits				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Congruence (-1) as the reference					
Unknown(0)	-912.15	-23,179.52	-65,455.52	-124,437.20	-2,209.55
	(1,183.42)	(27,536.04)	(71,976.89)	(187,489.80)	(14,810.07)
Incongruence(1)	-517.39	-28,624.32	-53,798.63	-99,515.74	-10,313.98
	(1,284.41)	(29,886.07)	(78,119.69)	(203,490.90)	(16,074.02)
Policy Information: Pre-emergency (0) as the reference					
State Emergency (1)	-13,836.35***	-313,138.80***	-854,823.90***	-2,480,539.00***	-126,632.60***
	(2,641.93)	(61,473.12)	(160,685.60)	(418,563.60)	(33,062.89)
Non-essential Close (2)	-15,774.32***	-299,603.80***	-936,370.10***	-2,702,840.00***	-296,525.40***
	(2,646.90)	(61,588.79)	(160,987.90)	(419,351.20)	(33,125.11)
First Phase Re-opening (3)	-17,804.95***	-285,794.30***	-1,039,514.00***	-3,083,799.00***	-294,985.90***
	(2,574.28)	(59,898.89)	(156,570.70)	(407,844.80)	(32,216.20)
Second Phase Re-opening (4)	-14,453.33***	-167,296.60***	-822,525.80***	-2,808,761.00***	-276,167.20***
	(2,539.42)	(59,087.90)	(154,450.80)	(402,322.90)	(31,780.02)
Third Phase Re-opening (5)	-13,486.20***	-106,771.20*	-732,069.00***	-2,712,136.00***	-279,286.90***
	(2,532.80)	(58,933.89)	(154,048.30)	(401,274.30)	(31,697.19)
Fourth Phase Re-opening (6)	-10,266.67***	-25,104.85	-627,744.50***	-2,434,325.00***	-183,246.20***
	(2,217.37)	(51,594.21)	(134,863.00)	(351,299.20)	(27,749.59)
Factual Information (3-day lag)					
COVID-19 cases	1.56***	17.39	94.24***	352.96***	-9.43
	(0.53)	(12.33)	(32.24)	(83.97)	(6.63)
COVID-19 deaths	-18.32***	-441.54***	-1,191.70***	-3,410.47***	-12.06
	(4.99)	(116.06)	(303.37)	(790.23)	(62.42)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	-588.49	-192,843.80***	153,295.30***	-103,726.00	-21,673.02**
	(819.23)	(19,061.99)	(49,826.45)	(129,791.00)	(10,252.36)
Constant	23,610.31***	785,214.20***	1,580,326.00***	3,521,536.00***	397,238.80***
	(2,497.01)	(58,101.06)	(151,871.30)	(395,603.60)	(31,249.25)
Observations	214	214	214	214	214
R^2	0.37	0.70	0.40	0.32	0.61
Note:					*p<0.1; **p<0.05; ***p<0.01

Figure 1: Summaries of Robustness Checks

	Robustness Check	Description	Result
1	Alternative Outcomes	Subtract the means of visits and ridership between March 20th and May 14th, 2020, excluding weekends and holidays, from the original values of visits and ridership in the baseline models (Appendix Table 1)	✔
2	Alternative Politicians' Information Congruence	Change the baseline politicians' information congruence [-1, 1] to alternative politicians' information congruence from both supporting re-open (-3) to both supporting prevention (3) (Appendix Table 2)	✔
3	Original Politicians' Information Congruence * Two Policy Stages	Create the interaction term of original politicians' information congruence [-1, 1] * two policy stages (pre-reopen = 0, reopen = 1) (Appendix Table 3)	☑
4	Alternative Politicians' Information Congruence * Two Policy Stages	Create the interaction term of alternative politicians' information congruence [-3, 3] * two policy stages (pre-reopen = 0, reopen = 1) (Appendix Table 4)	☑
5	One Day-lagged Facts	Use one-day lagged facts (Appendix Table 5)	✔
6	Two Day-lagged Facts	Use two-day lagged facts (Appendix Table 6)	✔
7	President's Message	Use only the President's message [-1, 1] (Appendix Table 7)	✔
8	Governor's Message	Use only the Governor's message [-1, 1] (Appendix Table 8)	✔

✔ means a full confirmation of the baseline results. ☑ means a great degree confirmation of the baseline results.

Appendices

Table 1: Effects of Different Types of Information on Voluntary Travel Adjustments

	NYC Visits				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Congruence (-1) as the reference					
Unknown(0)	-912.15	-23,179.52	-65,455.52	-124,437.20	-2,209.55
	(1,183.42)	(27,536.04)	(71,976.89)	(187,489.80)	(14,810.07)
Incongruence(1)	-517.39	-28,624.32	-53,798.63	-99,515.74	-10,313.98
	(1,284.41)	(29,886.07)	(78,119.69)	(203,490.90)	(16,074.02)
Policy Information: Pre-emergency (0) as the reference					
State Emergency (1)	$-13,836.35^{***}$	$-313,138.80^{***}$	$-854,823.90^{***}$	$-2,480,539.00^{***}$	$-126,632.60^{***}$
	(2,641.93)	(61,473.12)	(160,685.60)	(418,563.60)	(33,062.89)
Non-essential Close (2)	$-15,774.32^{***}$	$-299,603.80^{***}$	$-936,370.10^{***}$	$-2,702,840.00^{***}$	$-296,525.40^{***}$
	(2,646.90)	(61,588.79)	(160,987.90)	(419,351.20)	(33,125.11)
First Phase Re-opening (3)	$-17,804.95^{***}$	$-285,794.30^{***}$	$-1,039,514.00^{***}$	$-3,083,799.00^{***}$	$-294,985.90^{***}$
	(2,574.28)	(59,898.89)	(156,570.70)	(407,844.80)	(32,216.20)
Second Phase Re-opening (4)	$-14,453.33^{***}$	$-167,296.60^{***}$	$-822,525.80^{***}$	$-2,808,761.00^{***}$	$-276,167.20^{***}$
	(2,539.42)	(59,087.90)	(154,450.80)	(402,322.90)	(31,780.02)
Third Phase Re-opening (5)	$-13,486.20^{***}$	$-106,771.20^{*}$	$-732,069.00^{***}$	$-2,712,136.00^{***}$	$-279,286.90^{***}$
	(2,532.80)	(58,933.89)	(154,048.30)	(401,274.30)	(31,697.19)
Fourth Phase Re-opening (6)	$-10,266.67^{***}$	-25,104.85	$-627,744.50^{***}$	$-2,434,325.00^{***}$	$-183,246.20^{***}$
	(2,217.37)	(51,594.21)	(134,863.00)	(351,299.20)	(27,749.59)
Factual Information (3-day lag)					
COVID-19 cases	1.56^{***}	17.39	94.24^{***}	352.96^{***}	-9.43
	(0.53)	(12.33)	(32.24)	(83.97)	(6.63)
COVID-19 deaths	-18.32^{***}	-441.54^{***}	$-1,191.70^{***}$	$-3,410.47^{***}$	-12.06
	(4.99)	(116.06)	(303.37)	(790.23)	(62.42)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	$3,613.51^{***}$	$61,891.20^{***}$	$153,295.30^{***}$	151,066.00	$42,105.98^{***}$
	(819.23)	(19,061.99)	(49,826.45)	(129,791.00)	(10,252.36)
Constant	$13,422.38^{***}$	$329,146.50^{***}$	$888,498.30^{***}$	$2,518,216.00^{***}$	$298,174.60^{***}$
	(2,497.01)	(58,101.06)	(151,871.30)	(395,603.60)	(31,249.25)
Observations	214	214	214	214	214
R^2	0.43	0.65	0.40	0.34	0.62
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2: Effects of Different Types of Information (Detailed Politicians' Information) on Coproduction Activities

	NYC Visits				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Both re-open (-3) as the reference					
One re-open, the other unknown (-2)	930.62	8,557.45	37,836.00	153,789.50	-18,911.36
	(2,858.92)	(66,631.32)	(174,361.30)	(451,318.80)	(35,732.34)
One re-open, the other disagreed (-1)	268.58	-4,879.11	48,649.95	164,025.50	8,878.19
	(2,832.62)	(66,018.32)	(172,757.20)	(447,166.70)	(35,403.61)
Both Unknown (0)	978.81	10,491.60	27,995.07	331,471.30	-14,877.59
	(2,778.51)	(64,757.36)	(169,457.50)	(438,625.80)	(34,727.39)
One Prevention, the other disagreed (1)	2,732.50	60,002.94	140,288.80	341,680.70	-30,416.51
	(4,592.33)	(107,031.10)	(280,079.70)	(724,961.60)	(57,397.52)
One Prevention, the other Unknown (2)	-264.42	-15,862.37	-17,975.97	37,638.90	-7,734.68
	(2,720.20)	(63,398.32)	(165,901.10)	(429,420.50)	(33,998.58)
Both Prevention (3)	-568.58	-20,181.67	13,843.39	47,106.13	-7,070.82
	(2,985.37)	(69,578.53)	(182,073.60)	(471,281.40)	(37,312.84)
Policy Information: Pre-emergency (0) as the reference					
State Emergency (1)	$-12,927.48^{***}$	$-295,636.80^{***}$	$-828,094.60^{***}$	$-2,292,495.00^{***}$	$-130,665.00^{***}$
	(2,709.93)	(63,158.93)	(165,274.70)	(427,799.00)	(33,870.21)
Non-essential Close (2)	$-15,505.49^{***}$	$-298,818.90^{***}$	$-941,621.20^{***}$	$-2,585,433.00^{***}$	$-302,963.70^{***}$
	(2,740.83)	(63,879.18)	(167,159.50)	(432,677.60)	(34,256.46)
First Phase Re-opening (3)	$-17,338.36^{***}$	$-281,093.30^{***}$	$-1,044,959.00^{***}$	$-2,954,493.00^{***}$	$-306,503.80^{***}$
	(2,670.72)	(62,245.06)	(162,883.30)	(421,609.00)	(33,380.12)
Second Phase Re-opening (4)	$-14,426.39^{***}$	$-169,323.00^{***}$	$-826,989.40^{***}$	$-2,764,970.00^{***}$	$-278,488.00^{***}$
	(2,581.14)	(60,157.21)	(157,419.80)	(407,467.20)	(32,260.47)
Third Phase Re-opening (5)	$-13,430.32^{***}$	$-105,769.20^{*}$	$-733,115.90^{***}$	$-2,653,209.00^{***}$	$-279,281.30^{***}$
	(2,571.16)	(59,924.66)	(156,811.20)	(405,892.10)	(32,135.77)
Fourth Phase Re-opening (6)	$-9,755.84^{***}$	-20,123.56	$-620,144.40^{***}$	$-2,323,255.00^{***}$	$-192,035.10^{***}$
	(2,245.49)	(52,334.52)	(136,949.30)	(354,481.30)	(28,065.41)
Factual Information					
COVID-19 cases	1.85^{***}	24.81^{*}	107.42^{***}	381.48^{***}	-9.82
	(0.55)	(12.86)	(33.65)	(87.10)	(6.90)
COVID-19 deaths	-19.84^{***}	-480.26^{***}	$-1,246.14^{***}$	$-3,568.47^{***}$	-3.83
	(5.11)	(119.12)	(311.71)	(806.85)	(63.88)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	-639.71	$-195,073.90^{***}$	$152,415.50^{***}$	-111,477.30	$-22,967.96^{**}$
	(835.36)	(19,469.21)	(50,947.15)	(131,872.20)	(10,440.74)
Constant	$22,175.61^{***}$	$762,165.20^{***}$	$1,502,895.00^{***}$	$3,169,951.00^{***}$	$408,606.10^{***}$
	(3,574.98)	(83,320.33)	(218,033.20)	(564,359.70)	(44,682.15)
Observations	214	214	214	214	214
R^2	0.38	0.70	0.40	0.33	0.62
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3: Effects of Political Information Congruence at the Reopen Stage on Coproduction Activities

	NYC Visits				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Congruence (-1) as the reference					
Unknown(0)	-211.87	-3,404.56	32.05	-2,982.29	27,822.30
	(1,708.63)	(41,802.61)	(102,304.10)	(264,492.60)	(24,147.39)
Incongruence(1)	-2,032.26	-47,705.49	-118,144.30	-320,440.10	-24,552.53
	(2,080.72)	(50,906.14)	(124,583.40)	(322,092.30)	(29,406.06)
Policy Information: Pre-reopen (0) as the reference					
Re-open(1)	-753.92	155,089.40**	16,766.04	-617,888.10	18,701.39
	(2,716.48)	(66,460.31)	(162,649.30)	(420,506.30)	(38,390.97)
Politicians' information incongruence * Policy re-opening stage					
Unknown X reopen	-531.14	-21,328.43	-77,674.50	-38,181.90	-92,325.80**
	(2,763.53)	(67,611.43)	(165,466.40)	(427,789.60)	(39,055.91)
Incongruence X reopen	2,702.19	44,128.13	93,964.34	395,798.10	-20,453.46
Factual Information					
COVID-19 cases	0.70	0.91	45.31	209.17**	-21.90***
	(0.59)	(14.48)	(35.44)	(91.62)	(8.36)
COVID-19 deaths	-22.67***	-504.45***	-1,413.67***	-3,914.37***	-238.20***
	(5.22)	(127.75)	(312.65)	(808.31)	(73.80)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	57.05	-179,148.00***	191,808.50***	4,843.31	-14,409.66
	(926.27)	(22,661.77)	(55,460.48)	(143,385.10)	(13,090.63)
	(3,064.59)	(74,977.03)	(183,492.40)	(474,393.10)	(43,310.67)
Constant	12,030.46***	546,423.70***	856,607.20***	1,450,647.00***	217,600.50***
	(1,871.86)	(45,796.21)	(112,077.70)	(289,760.80)	(26,454.30)
Observations	214	214	214	214	214
R^2	0.18	0.56	0.24	0.15	0.36
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4: Effects of Political Information Incongruence at the Reopen Stage on Coproduction Activities

	NYC Visits				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Both re-open (-3) as the reference					
One re-open, the other unknown (-2)	2,220.73	51,794.29	145,539.30	289,092.40	34,080.26
	(4,683.19)	(115,809.40)	(276,550.90)	(702,693.00)	(65,657.91)
One re-open, the other disagreed (-1)	3,797.85	76,305.75	279,171.10	733,492.50	44,412.95
	(4,789.68)	(118,442.80)	(282,839.50)	(718,671.60)	(67,150.91)
Both Unknown (0)	9,583.82**	185,687.30*	657,349.60**	1,855,113.00***	131,756.20**
	(4,447.73)	(109,986.60)	(262,646.20)	(667,362.30)	(62,356.69)
One Prevention, the other disagreed (1)	4,839.11	120,426.50	305,745.50	637,766.10	30,628.43
	(5,859.84)	(144,906.30)	(346,034.00)	(879,243.60)	(82,154.36)
One Prevention, the other Unknown (2)	2,678.25	59,574.56	182,520.70	416,897.50	120,757.50**
	(4,270.76)	(105,610.50)	(252,196.10)	(640,809.40)	(59,875.65)
Both Prevention (3)	3,019.34	52,655.28	234,263.80	564,994.90	88,390.87
	(4,480.14)	(110,788.20)	(264,560.50)	(672,226.30)	(62,811.18)
Policy Information: Pre-reopen (0) as the reference					
Re-open(1)	3,927.03	259,055.40*	346,774.50	138,809.60	73,045.51
	(5,849.16)	(144,642.30)	(345,403.50)	(877,641.60)	(82,004.67)
Politicians' information incongruence * Policy re-opening stage					
One re-open, the other unknown X Reopen	-2,701.00	-94,124.45	-231,554.50	-280,301.40	-94,141.86
	(6,378.55)	(157,733.40)	(376,664.90)	(957,074.20)	(89,426.66)
One re-open, the other disagreed X Reopen	-4,576.66	-117,085.90	-359,024.50	-747,117.30	-49,893.37
	(6,408.13)	(158,464.80)	(378,411.30)	(961,511.80)	(89,841.30)
Both Unknown X Reopen	-9,749.89	-199,152.30	-773,523.40**	-1,794,353.00*	-168,377.80*
	(6,143.00)	(151,908.50)	(362,755.00)	(921,730.40)	(86,124.22)
One Prevention, the other Unknown X Reopen	-2,799.24	-82,016.63	-250,778.00	-376,047.20	-154,327.80*
	(5,968.78)	(147,600.20)	(352,466.90)	(895,589.30)	(83,681.66)
Both Prevention X Reopen	-4,165.17	-90,833.13	-270,409.10	-644,830.30	-36,579.29
	(6,590.86)	(162,983.60)	(389,202.20)	(988,930.60)	(92,403.24)
Factual Information					
COVID-19 cases	0.96	7.57	57.44	243.55***	-29.07***
	(0.61)	(15.03)	(35.88)	(91.17)	(8.52)
COVID-19 deaths	-24.36***	-552.94***	-1,486.61***	-4,087.47***	-193.41**
	(5.47)	(135.39)	(323.30)	(821.49)	(76.76)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	-160.03	-185,006.50***	179,700.00***	-36,017.29	-16,153.14
	(934.91)	(23,119.04)	(55,207.91)	(140,278.70)	(13,107.30)
Constant	7,520.38*	454,779.60***	557,129.90**	684,949.80	141,151.10**
	(4,265.34)	(105,476.40)	(251,875.90)	(639,995.80)	(59,799.63)
Observations	214	214	214	214	214
R^2	0.22	0.58	0.30	0.24	0.40

Note: One Prevention, the other disagreed (1) X Stage reopen was omitted because of lacking observations. *p<0.1; **p<0.05; ***p<0.01

Table 5: Effects of Different Types of Information on NYC Visits (one-day lag)

	NYC Visits				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Congruence (-1) as the reference					
Unknown(0)	-1,076.98	-24,685.46	-75,504.46	-177,999.60	3,235.11
	(1,118.27)	(26,256.71)	(67,897.48)	(176,121.80)	(14,553.87)
Incongruence(1)	-601.93	-29,537.66	-59,165.09	-135,112.90	-5,217.26
	(1,223.04)	(28,716.84)	(74,259.18)	(192,623.60)	(15,917.50)
Policy Information: Pre-emergency (0) as the reference					
State Emergency (1)	-13,136.63***	-304,070.00***	-811,684.10***	-2,310,230.00***	-134,508.00***
	(2,514.94)	(59,050.43)	(152,699.10)	(396,091.90)	(32,731.15)
Non-essential Close (2)	-14,696.72***	-271,428.70***	-867,539.90***	-2,480,197.00***	-304,578.90***
	(2,577.90)	(60,528.60)	(156,521.50)	(406,007.00)	(33,550.49)
First Phase Re-opening (3)	-17,455.06***	-276,684.20***	-1,016,852.00***	-3,009,981.00***	-297,792.90***
	(2,485.16)	(58,351.16)	(150,890.90)	(391,401.40)	(32,343.55)
Second Phase Re-opening (4)	-14,250.49***	-162,158.90***	-809,465.10***	-2,766,704.00***	-277,542.90***
	(2,451.15)	(57,552.72)	(148,826.10)	(386,045.70)	(31,900.98)
Third Phase Re-opening (5)	-13,289.12***	-102,813.50*	-719,588.00***	-2,667,133.00***	-281,311.20***
	(2,442.62)	(57,352.37)	(148,308.10)	(384,701.80)	(31,789.93)
Fourth Phase Re-opening (6)	-10,178.32***	-22,874.64	-621,816.50***	-2,409,509.00***	-185,559.70***
	(2,137.58)	(50,190.12)	(129,787.10)	(336,659.70)	(27,819.96)
Factual Information (one-day lag)					
COVID-19 cases	1.76***	16.39	104.86***	371.33***	-1.59
	(0.49)	(11.53)	(29.81)	(77.31)	(6.39)
COVID-19 deaths	-24.55***	-530.71***	-1,561.04***	-4,451.34***	-64.45
	(4.51)	(105.83)	(273.68)	(709.91)	(58.66)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	440.26	-181,734.40***	215,337.40***	125,291.20	-26,588.15***
	(751.24)	(17,638.90)	(45,612.60)	(118,316.20)	(9,777.09)
Constant	22,920.50***	777,495.20***	1,538,835.00***	3,384,880.00***	395,864.90***
	(2,421.76)	(56,862.50)	(147,041.30)	(381,415.90)	(31,518.40)
Observations	214	214	214	214	214
R^2	0.42	0.71	0.44	0.37	0.61
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6: Effects of Different Types of Information on NYC Visits (two-day lag)

	Dependent variable:				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Congruence (-1) as the reference					
Unknown(0)	-975.92	-22,864.78	-66,156.12	-153,398.20	2,246.83
	(1,126.87)	(26,514.74)	(68,231.56)	(176,960.50)	(14,568.23)
Incongruence(1)	-654.56	-29,095.52	-59,439.78	-143,912.50	-5,874.92
	(1,225.39)	(28,832.80)	(74,196.75)	(192,431.40)	(15,841.87)
Policy Information: Pre-emergency (0) as the reference					
State	-13,644.05***	-310,025.10***	-846,508.00***	-2,421,505.00***	-132,744.50***
Emergency (1)	(2,543.19)	(59,839.82)	(153,988.50)	(399,373.50)	(32,878.33)
Non-essential	-15,416.84***	-286,569.20***	-925,270.10***	-2,634,932.00***	-302,421.50***
Close (2)	(2,581.59)	(60,743.32)	(156,313.50)	(405,403.50)	(33,374.74)
First Phase	-17,669.43***	-281,619.40***	-1,033,930.00***	-3,054,389.00***	-297,293.70***
Re-opening (3)	(2,499.47)	(58,811.06)	(151,341.10)	(392,507.60)	(32,313.09)
Second Phase	-14,373.08***	-164,850.70***	-819,045.20***	-2,792,168.00***	-277,279.00***
Re-opening (4)	(2,466.69)	(58,039.88)	(149,356.60)	(387,360.70)	(31,889.37)
Third Phase	-13,449.93***	-105,517.90*	-731,328.10***	-2,701,348.00***	-280,871.50***
Re-opening (5)	(2,459.25)	(57,864.93)	(148,906.40)	(386,193.10)	(31,793.25)
Fourth Phase	-10,247.02***	-24,323.59	-627,807.70***	-2,424,919.00***	-185,098.00***
Re-opening (6)	(2,151.76)	(50,629.74)	(130,287.80)	(337,905.10)	(27,817.95)
Factual Information (Two-day lag)					
COVID-19 cases	1.90***	20.12*	120.46***	405.83***	-3.61
	(0.49)	(11.47)	(29.52)	(76.55)	(6.30)
COVID-19 deaths	-23.34***	-515.67***	-1,515.96***	-4,247.18***	-50.73
	(4.62)	(108.78)	(279.92)	(725.99)	(59.77)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	-127,43	-187,310.10***	180,332.30***	4,464.91	-25,714.02***
	(757.67)	(17,827.45)	(45,876.17)	(118,981.20)	(9,795.10)
Constant	23,291.43***	780,307.20***	1,558,582.00***	3,460,730.00***	396,128.60***
	(2,427.28)	(57,112.70)	(146,970.70)	(381,172.60)	(31,379.94)
Observations	214	214	214	214	214
R^2	0.41	0.71	0.44	0.37	0.61
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: Effects of Trump's Tweets on NYC Visits

	NYC Visits				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Trump Tweets: Reopen (-1) as the reference					
No Information (0)	-493.71	-2,113.86	-43,363.35	-38,302.21	-16,312.36
	(935.40)	(21,809.30)	(56,937.66)	(148,220.80)	(11,671.51)
Prevention (1)	-1,272.09	-14,721.09	-40,477.89	-155,378.50	-10,730.17
	(1,469.69)	(34,266.55)	(89,459.86)	(232,882.90)	(18,338.16)
Policy Information: Pre-emergency (0) as the reference					
State Emergency (1)	-13,317.70***	-303,826.90***	-840,256.80***	-2,408,194.00***	-129,633.50***
	(2,659.00)	(61,995.82)	(161,852.80)	(421,337.10)	(33,177.82)
Non-essential Close (2)	-15,708.25***	-299,862.40***	-943,185.90***	-2,692,831.00***	-303,265.60***
	(2,651.28)	(61,815.71)	(161,382.60)	(420,113.00)	(33,081.43)
First Phase Re-opening (3)	-17,870.33***	-288,664.60***	-1,055,131.00***	-3,090,205.00***	-305,511.60***
	(2,589.48)	(60,374.82)	(157,620.90)	(410,320.40)	(32,310.32)
Second Phase Re-opening (4)	-14,501.30***	-168,296.00***	-828,607.40***	-2,813,431.00***	-280,884.00***
	(2,543.67)	(59,306.83)	(154,832.70)	(403,062.20)	(31,738.77)
Third Phase Re-opening (5)	-13,543.54***	-108,080.80*	-734,749.10***	-2,720,287.00***	-279,465.10***
	(2,532.20)	(59,039.40)	(154,134.50)	(401,244.60)	(31,595.65)
Fourth Phase Re-opening (6)	-10,208.36***	-27,416.00	-632,828.00***	-2,430,886.00***	-190,818.50***
	(2,200.59)	(51,307.66)	(133,949.20)	(348,698.00)	(27,457.92)
Factual Information					
COVID-19 cases	1.75***	21.78*	103.40***	380.72***	-8.83
	(0.53)	(12.25)	(31.97)	(83.23)	(6.55)
COVID-19 deaths	-19.13***	-461.36***	-1,220.55***	-3,533.91***	-13.09
	(5.01)	(116.88)	(305.13)	(794.32)	(62.55)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	-667.42	-195,130.30***	150,918.40***	-116,730.30	-21,735.06***
	(821.35)	(19,150.16)	(49,995.42)	(130,148.60)	(10,248.44)
Constant	23,257.09***	766,041.60***	1,560,188.00***	3,446,160.00***	411,391.60***
	(2,404.87)	(56,070.51)	(146,383.60)	(381,067.40)	(30,006.82)
Observations	214	214	214	214	214
R^2	0.37	0.70	0.40	0.32	0.62
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 8: Effects of Cuomo's Tweets on NYC Visits

	NYC Visits				
	Access A Ride	Bridges and Tunnels	Buses	Subways	Visits
	(1)	(2)	(3)	(4)	(5)
Politicians' Information: Cuomo Tweets: Reopen (-1) as the reference					
No Information (0)	466.70	-5,499.17	-28,920.52	92,892.21	-3,591.59
	(1,327.28)	(30,898.52)	(80,762.53)	(210,168.10)	(16,513.98)
Prevention (1)	-24.51	-14,409.74	-825.65	23,593.30	13,518.88
	(1,181.60)	(27,507.19)	(71,898.26)	(187,100.70)	(14,701.45)
Policy Information: Pre-emergency (0) as the reference					
State	-13,214.61***	-303,212.70***	-857,951.00***	-2,394,525.00***	-137,979.80***
Emergency (1)	(2,701.04)	(62,878.97)	(164,353.00)	(427,695.40)	(33,606.21)
Non-essential	-15,285.80***	-299,062.30***	-953,400.20***	-2,631,829.00***	-306,499.20***
Close (2)	(2,739.64)	(63,777.62)	(166,701.90)	(433,807.90)	(34,086.50)
First Phase	-17,274.36***	-284,820.80***	-1,058,237.00***	-3,012,883.00***	-307,980.80***
Re-opening (3)	(2,659.18)	(61,904.59)	(161,806.20)	(421,067.80)	(33,085.44)
Second Phase	-14,130.44***	-168,665.50***	-833,211.20***	-2,757,376.00***	-280,574.00***
Re-opening (4)	(2,602.32)	(60,580.87)	(158,346.20)	(412,064.00)	(32,377.97)
Third Phase	-13,277.32***	-106,803.70*	-748,577.40***	-2,676,185.00***	-284,650.80***
Re-opening (5)	(2,580.10)	(60,063.53)	(156,994.00)	(408,545.10)	(32,101.47)
Fourth Phase	-9,781.91***	-22,800.40	-639,146.00***	-2,376,211.00***	-195,888.20***
Re-opening (6)	(2,257.30)	(52,548.82)	(137,352.00)	(357,430.90)	(28,085.17)
Factual Information					
COVID-19 cases	1.65***	21.54*	102.86***	363.71***	-9.69
	(0.52)	(12.14)	(31.73)	(82.58)	(6.49)
COVID-19 deaths	-18.63***	-457.48***	-1,220.27***	-3,452.90***	-12.01
	(4.97)	(115.78)	(302.62)	(787.52)	(61.88)
Weekdays: Weekends and holidays (0) as the reference					
Weekdays(1)	-558.95	-194,144.90***	147,223.30***	-99,082.44	-23,314.89***
	(825.83)	(19,225.03)	(50,250.36)	(130,766.40)	(10,274.98)
Constant	22,288.46***	770,091.50***	1,544,144.00***	3,311,857.00***	397,138.00***
	(2,598.56)	(60,493.27)	(158,117.20)	(411,468.10)	(32,331.14)
Observations	214	214	214	214	214
R^2	0.37	0.70	0.40	0.32	0.62
Note:					*p<0.1; **p<0.05; ***p<0.01