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KOÇ UNIVERSITY-TÜSİAD ECONOMIC RESEARCH FORUM
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**POLARIZED POLITICS OF PANDEMIC RESPONSE
AND THE COVID-19 CONNECTEDNESS ACROSS
THE U.S. STATES**

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Polarized Politics of Pandemic Response and the Covid-19 Connectedness Across the U.S. States*

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November 13, 2020

Abstract

This paper investigates the state-level differences in government and community responses to the Covid-19 pandemic, leading to different growth trajectories of Covid-19 cases and their connectedness across the U.S. states. Our regression analysis shows that higher growth trajectories are observed in the states that implemented the lax government and community response to the pandemic. Moving to the analysis of spillovers/connectedness of Covid-19 cases across the states, we apply the Diebold-Yilmaz connectedness methodology to the growth rates of Covid-19 cases. Using the total directional connectedness measures, we find that the states with lax government and community response generated connectedness of Covid-19 cases to others. These findings are also supported by the secondary regression analysis of pairwise connectedness measures over time. Finally, the travel intensity between the pairs of states, indirectly measured by the data on smartphone location exposure, contributes significantly to the pairwise directional connectedness of Covid-19 across the states.

JEL codes: I10; I18

Key Words: Covid-19, Coronavirus, Spillovers, Connectedness, Government policy stringency, Community mobility, Travel Intensity.

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1 Introduction

Covid-19 pandemic has shaken the roots of the modern welfare state and society in several weeks. Governments worldwide were caught unprepared to contain the spread of a new virus that quickly turned into a pandemic; it infected more than 47 million and killed more than 1.2 million people around the world as of November 3.

The government response to Covid-19 has been the most critical element that has shaped how the pandemic evolved in various parts of the world. Once the virus struck, the policies to contain it ranged from recommending strict social distancing to closures of daycares, schools, and public gatherings and to effectively locking down entire regions and sometimes the whole nations for a specified period.

The trade-off between strict public health measures to contain the virus and the continuation of economic activity has forced policymakers to strike a balance between the two, which has proven to be rather tricky. Countries with efficient health systems such as Germany could spare their citizens from a complete lockdown. Others, such as Italy and Spain, whose health systems were not as efficient, implemented regional and national lockdown measures.

The situation in the United States, on the other hand, was quite different. The existence of an effective healthcare system and warnings received in advance provided ample time to respond to the pandemic at an early stage. However, the U.S. federal government was slow, disorganized, and even reluctant to stage an effective response to the pandemic. Consequently, it received widespread criticisms from domestic and international organizations and experts for the lack of federal leadership and assistance to states, delays in testing, and misleading public statements.

The U.S. federal government's response to criticisms politicized the whole process. While many coastal states that got severely hit in March responded immediately to the pandemic, some others have just followed the federal government, downplaying the seriousness of the public health threat posed by the virus. Sharp differences of opinion and policy response competed and survived in the last six months. They led to the formation of demarcation lines across the party lines in a year of presidential elections.

In this paper, we focus on both the government and community response to the pandemic at the state-level and how critical they have been for the wide variation in the new coronavirus case trajectories.¹ The availability of daily big data sets made it possible to link the differences in Covid-19 case trajectories and the transmission of

¹ In general, the literature has focused on government policy response (school closures, cancellation of public meetings, stay-at-home orders, etc.) as the most critical element of containment efforts (see, for example, Alexander and Karger (2020)). However, recently, Goolsbee and Syverson (2020) shows that individuals' voluntary decisions to disengage from commerce played a significant role in the decline in economic activity.

infections across states to government and community response at the state level.

In the literature, many studies interpret the transmission dynamics of the Covid-19 outbreak maintaining certain assumptions of different structural models. In many cases, these models do not elicit convincing empirical evidence on the transmission of the virus; they usually concentrate on the partial impact of different responses to the course of the pandemic. On the other hand, connectedness analysis, which has been widely used in empirical financial and economic network studies, offers a rather global approach to approximate the linkages among the variables using multivariate time series techniques. It is comparatively useful when the structural models are limitedly available to constitute a complete approach to the underlying linkages. Therefore, we choose to study the regional connectedness in the United States because there has been substantial variation in the public health policy measures across the states from the beginning onwards. The absence of leadership from the federal government in spearheading a joint policy drive and coordination resulted in relatively high rates of increases in many states, which in time took an irregularly-shaped distribution of total and new cases across the states.

The connectedness analysis of new cases' growth provides further empirical evidence on the dissociation between the pandemic's course in states along the party lines. At the next step, secondary regressions are used to investigate the potential determinants of Covid-19 connectedness across states. Secondary regressions reveal the pairwise impact of the community mobility, i.e., the use of public or private spaces, state government policy stringency, and the travel intensity between states on the connectedness of Covid-19 across states. Even more importantly, the secondary regression analysis shows that the governor's party affiliation can be a contributing factor to the Covid-19 connectedness to other states.

In the next section, we briefly review the literature and pose the contributions of this paper to the literature on Covid-19. In section 3, we introduce the data and briefly summarize how the pandemic progress at the national level. We also show that governors' party affiliation also contributes to the state-level government response and the resulting differences in new cases' growth rates. Section 4 analyzes the dynamic system-wide and directional connectedness measures that will help us understand the transmission of new infections across states over time. Section 5 analyzes factors that contributed to the pairwise connectedness of Covid-19 across states over time. Section 6 concludes the paper.

2 Literature Review

Since March, economists around the world turned their attention to the study of Covid-19 and its economic impact.² The broad consensus on the strong link between the course of the epidemic and its potential economic impact has prompted economists to visit epidemiological models, the Susceptible-Infected-Recovered (SIR) model of Kermack and McKendrick (1927), in particular.

Eichenbaum et al. (2020) extend the SIR model by incorporating the aggregate demand and supply and show how containment policies can save many lives. Acemoglu et al. (2020) incorporate the SIR model with an age structure and show that the economic impact of the pandemic can be taken under control by restricting the 65+ years old from participating in social and economic activities. Among many other studies using the SIR model, Berger et al. (2020) and Wangping et al. (2020) focus on the transmission dynamics and derive policy recommendations. Gapen et al. (2020) focuses on the estimates of epidemiological model parameters to assess the effectiveness of different measures, including increased testing, masking requirements, and others, to slow down the transmission of Covid-19 in the United States. Finally, Favero (2020) applies the SIR model to the Italian case and shows that the strict application of the nationwide lockdown led the reproduction number of the virus (R_0) to drop from 2.2 to 0.95.

A majority of studies in the recent pandemic literature focus on the univariate intensity of the Covid-19 epidemic (such as cases and/or deaths) at the national/regional/municipal level. In this study, we introduce a multivariate framework that measures nationwide comovement of coronavirus spread. This approach is essential as the government's objective is to flatten the "total infected curve"; however, a proper policy action should also curb the regional spillovers. Regional spillovers have become more evident in the increase of Covid-19 cases in many U.S. states since mid-June in response to the relaxation of the containment measures.

We also build on the literature that investigates the effectiveness of policy responses to Covid-19. Several studies link how flattening the pandemic curve is related to different measures taken. Deb et al. (2020) relied on the "stringency index" to explain the number of confirmed cases and illustrate the significance of the timing of the containment measures. Furthermore, Alvarez et al. (2020) inspects the effectiveness of policy actions and conclude that they are likely to be successful if they were executed earlier.

Recent studies provide evidence on the critical importance of regional characteristics

² See Anyfantaki et al. (2020) and Brodeur et al. (2020) for well-structured literature reviews.

for the transmission of the virus. Bluhm and Pinkovskiy (2020) studies the regional differences in contagion and show that there is a sizeable discontinuity in Covid-19 cases at the the Inner German border between the East and West Germany. Furthermore, both the transmission of the virus and the community mobility vary substantially across different pairs of regions. Lattanzio and Palumbo (2020) compares the London and Lombardy regions to present whether different scenarios covering various mobility levels and dates of re-opening influence the observed and unobserved numbers of the infected. The distance among the two regions can also be a factor, as Valsecchi (2020) argues that diffusion of the Covid-19 is exploded by the internal migrants who traveled to their home towns across different regions in Italy.

Kuchler et al. (2020) focuses on the Lodi region and demonstrates how social networks correlates with the geographic spread in the region. In another contribution, Eckardt et al. (2020) test for treatment effects of border control in the Schengen Area and find that the border controls had a significant impact of limiting the pandemic. To the best of our knowledge, there was no such control in the U.S. across the borders of individual states.

There is also a growing literature on how political party affiliation and partisanship affects the individuals' responses to the pandemic. As those have been recently witnessed in many countries, the bitter race among the political actors in a highly-polarized domain put up a further challenge to applying sound governance principles to fight against the Covid-19 pandemic. Evidently, the ideological positioning of political parties, leaders, and their followers has a remarkable impact on the public attitude and belief on the course of the pandemic and the perception of the Covid-19 risk. Gadarian et al. (2020) find that the political difference based on partisanship is the only consistent factor that differentiates American people's political attitude towards the Covid-19 pandemic. Baker et al. (2020) review many poll outcomes from different sources and claim that Republican voters tend to be less concerned about the impact of the growing pandemic in the United States. Arguing that the demographic reasons behind the difference in the people's beliefs about the COVID pandemic are not evident, they also analyze the impact of heterogeneity of political party affiliations and other demographic factors on the consumer behavior during the Covid-19 pandemic. Their results indicate a marginal drop in community mobility in Republican states; people who live in Republican states have spent more time in restaurants and retail markets, while people in Democratic states cut their public transportation spending drastically.

Painter and Qiu (2020) argues that the differences in political beliefs limit the effectiveness of social distancing policies. Using geolocation data, they show that residents in Democratic states are more likely to follow the social distancing orders. Similarly, using the Governor's Twitter communications, publicly available Google

search and location data of individuals, Grossman et al. (2020) finds that political partisanship affects the voluntary engagement to the social distancing recommendations. Ajzenman et al. (2020) explores the effect of far-right President Jair Bolsonaro’s speeches and comments on the pandemic to the social distancing behavior of individuals in Brazil. They find that those communications played a crucial role in decreasing the social distancing behavior in pro-Bolsonaro municipalities. On the other hand, Calvillo et al. (2020) argues the partisan media coverage on Covid-19 mediates the ideology and the perception of Covid-19 risk.

The closest paper to ours in the literature is Rothert et al. (2020), which analyzes the effect of the state governments’ fragmented mitigation policies on the diffusion of Covid-19 cases across counties and states of the U.S. They use both spatial and time series econometric methods to show that the implementation of scattered lockdown policies contributed to the diffusion of the virus across counties and states. This paper differs from Rothert et al. (2020) in that we are using time series and panel estimations to analyze the differences in terms of the rate of increase in new infections across states. The use of time series and panel estimation framework allows us to analyze how the dynamics of Covid-19 cases and their connectedness across states have changed over time.

Despite the earlier work using similar data on government response and the social distancing behavior of individuals, our paper stands out from others. It shows that the Covid-19 cases spilled over from states that implemented lax policies, and the community’s attitude towards the pandemic was less accommodative. Furthermore, this paper is the first to identify the role of the governors’ political party affiliation in the implementation of public health policy measures against the pandemic.

3 State-level Government and Community Response

This section introduces the dataset and presents a further univariate analysis of how the growth of the new confirmed cases of Covid-19 progressed at the state-level and whether this progress had anything to do with the different responses to the pandemic.

3.1 Data

Our primary data of interest is the daily number of confirmed new cases of Covid-19, which is accessible at the Github page of *Johns Hopkins University Center for Systems Science and Engineering*. We are aware of the limitations of the data on daily confirmed new cases; due to reasons such as limited testing opportunities, the rate of asymptomatic people, political stance on reporting, the number of daily confirmed new cases is likely to

be different from the number of daily actual new cases or infections. The difference was perhaps even higher earlier in the pandemic when the daily number of tests conducted in the U.S. was very low (68,682 on March 21 and 127,428 on March 31) compared to the average daily number of tests conducted since the end of July (which is approximately 800,000).

The further irregularities in reporting such as the weekend effect, the political preference on the reporting day, different conventions on revisions and corrections, make daily new cases fluctuate significantly from one day to the other. In the literature, reporting, and analyzing the moving average of daily new cases to deal with irregular fluctuations, has been a standard treatment since the Covid-19 outbreak. The daily growth rates also contain the impairments in the reported data, Figure 1 illustrates the time-series of observed average growth rates of new cases across 51 states of the U.S. and the 7-day moving averages, starting from April 1 when the total cases hit a hundred in all states. The difference between the two series is apparent. While observed average new cases growth rate across states demonstrates huge swings due to irregularities in the reported data of new cases, 7-day moving average induces a more smooth and stable pattern.

Moving average is plausibly useful to surmount the short-term distortions in the data removing the irregularities generated by the reporting process; on the flip side, it averages out valuable short-term information in the dataset. However, it is still convenient to analyze the course of the Covid-19 pandemic capturing the emerging trends in the new cases. To summarize, we are working with the average daily growth rate of the 7-day average of the new confirmed cases in the multivariate analysis.

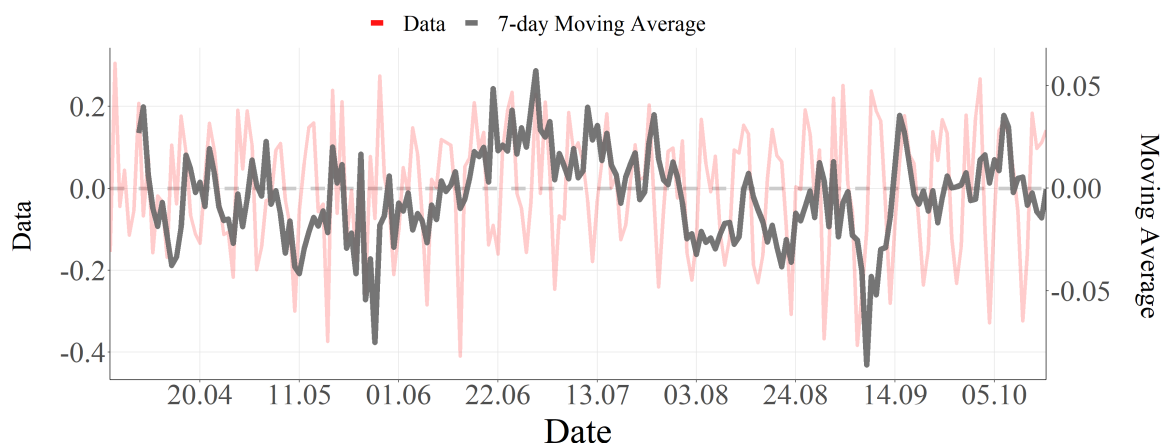


Figure 1: New Cases Growth – Observed Data vs. Moving Average (MA)

Along with the 7-day average growth rate of the daily new cases of Covid-19, we use the government policy stringency index (GSI) as a measure of government response to

the Covid-19 pandemic, which is developed by a group of researchers at the *Blavatnik School of Government, University of Oxford*. For a detailed account of the measurement framework see Hale et al. (2020).

It is essential to gauge how the government and the community response to the pandemic affected the nationwide and regional economic and social activity. In this regard, Google generated the *Google Community Mobility Indicators* dataset using the anonymous users' location histories aggregated for six distinct spaces: retail & recreation, groceries & pharmacies, parks, transit stations, workplaces, and residential areas for each day, each county and each state. While the first five variables measure the uses of alternative public spaces, an increase in the residential space use indicates a decline in public space use. All six measures are benchmarked to a control period (January through the first week of February) and cover the daily changes in community mobility in public and private places relative to the control period.

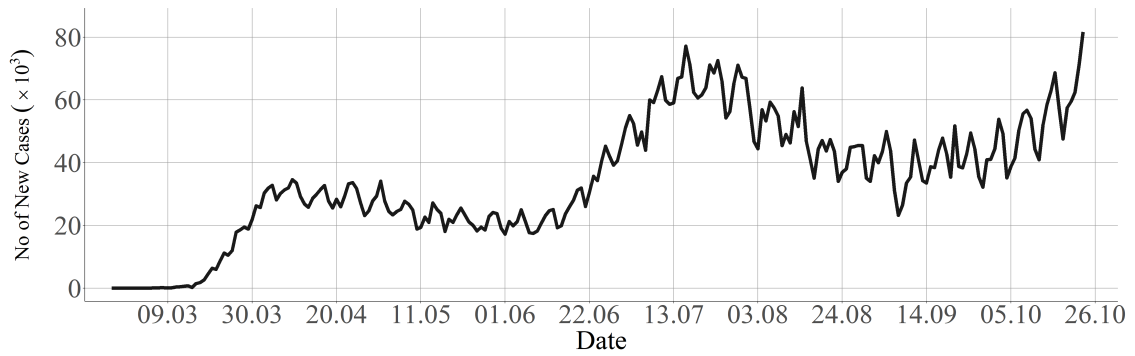
Finally, we use mobile phone exposure indices derived from *PlaceIQ movement data* to measure the mobility of phones and hence individuals across states irrespective of the distance. While the geodesic distance is a good measure of the movements across states through highway and/or railroads, the exposure indices would help measure highway, railroad, and air-based movements across states.

3.2 Covid-19 Pandemic At the National Level

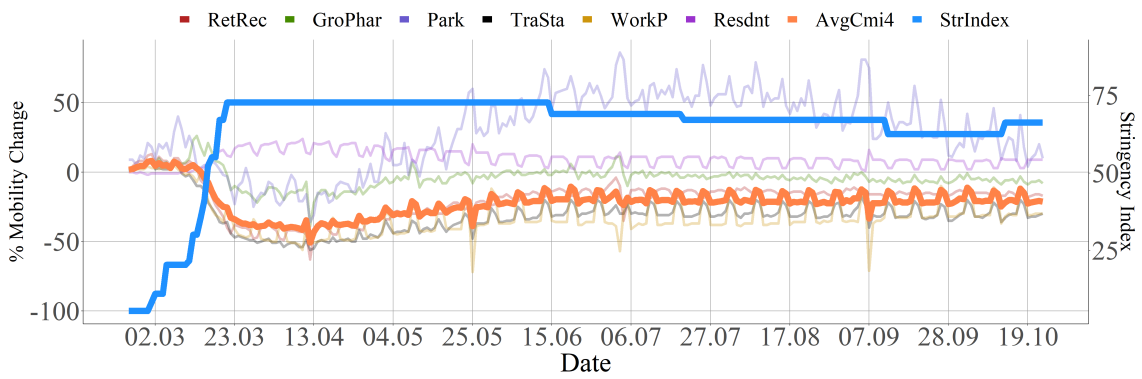
We start our empirical analysis with a brief overview of how the pandemic progressed in the U.S. and how the state governments and communities reacted to the pandemic. Figure 2(a) presents the number of daily confirmed new Covid-19 cases since the beginning of March. In just three weeks, the number of new cases increased rapidly from zero to reach several thousand by mid-March. As the number of Covid-19 cases started to grow in the Eastern and Western coastal states in mid-March, the federal and state governments responded by closing schools, canceling public events, asking federal employees to work from home while recommending other employees to do the same.

As a result of the tightening public health policy measures, the average stringency index across the U.S. states (see Figure 2(b)) climbed from less than 10 in the first week of March to 20 by the end of the second week and all the way to 75 by the end of the third week of March. This was the highest level achieved in the average stringency index.

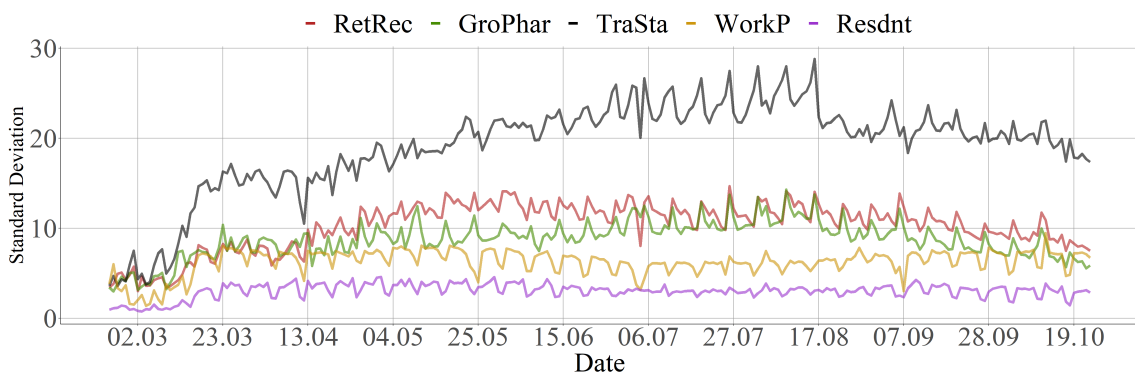
Figure 2(b) presents the average community mobility measures for the U.S, along with the average Covid-19 policy stringency index (GSI) for the state governments. Consistent with the rapid increase in the number of cases and more stringent policy response, communities also responded by reducing their mobility in public spaces while increasing their presence in their private residential spaces.



(a) Daily Number of New Covid-19 Infections



(b) Average Community Mobility Indices and Government Stringency Index



(c) Standard Deviation of Community Mobility Indices across Regions

Figure 2: United States – Daily New Cases of Covid-19 Virus, Federal Government Policy Response and Google Community Mobility Index

Despite the increased stringency of government policies, new daily Covid-19 cases continued to grow to reach 20 thousand by the end of March. Interestingly, even the number of new daily Covid-19 infections reached 30 thousand in early April; the U.S. federal government introduced no further measures. The government avoided imposing a nationwide lockdown, leaving the decision to state governments, many of which decided not to impose lockdowns. In the meantime, many European countries took strict measures to control the number of infections in April, the peak month, which pushed the government stringency index to as high as 90. It was bizarre not to observe a similar reaction by the U.S. government.³ Consequently, the stringency index for the U.S. stayed flat at 41.7 for a long time, before declining to 38 on July 30.

As Figure 2(b) illustrates, the drop in community mobility started towards the end of the second week of March but gained momentum only in the third week of March for the whole country. The average of four CMI measures (Avg.CMI4) indicates close to a 25-percent reduction in the community's use of public spaces by this time. It declined further to 60% of the average mobility level during the reference period, picking up pace gradually to reach around 75% in May, about 80% in June through August.

Community mobility in transit stations (TraSta) and workplaces (WorkP) declined close to 50% by the end of March. It fluctuated around that level (50-55%) in April, picking up pace gradually to reach around 70% of the mobility observed in January and the first week of February. In the meantime, the community activities in parks (Park), and groceries & pharmacies (GroPhar) started to decline only approximately 20%.

The other important measure of community mobility is the use of residential places (Resdnt). As individuals ended spending more time at home, the residential space indicator reached 20% higher in late March (compared to the reference period) and, on average, stayed around that level throughout April, declining gradually to 15% in May and 10% from June onwards.

As we have noted in the introduction, our objective in this paper is to go one step further and show that those states with less restricted community mobility experienced a faster growth rate of Covid-19 infections. Those states would experience a faster rate of increase of Covid-19 cases and more likely to spread the virus to other states. To gauge the variation in community mobility across regions, we present the standard deviation of CMIs across states in Figure 2(c).

Figure 2(c) is quite revealing. While the standard deviation of CMIs declined substantially in countries that instituted nationwide lockdowns to stem the spread of the Covid-19 virus in March and early April, in the U.S., it is the other way around:

³ Another major point of criticism of the Trump administration was the application of a rather low number of Covid-19 tests in the first two months of the pandemic, which perhaps kept the number of observed infections lower than what would have otherwise been the case.

The standard deviation of the CMIs increased, almost doubled in March. The standard deviation of transit stations, on the other hand, tripled during the same period. It increased from around 5 to 15 in mid-March and fluctuated around that level in April. The rise in standard deviations of CMIs in the second half of March results from the absence of a nationwide lockdown in the U.S. and the wide variation in policy reaction and hence community mobility across the 51 states.

3.3 Politicization of the Response and Pandemic Momentum

In the previous section, we discussed the development of the Covid-19 pandemic at the national level along with measures of policy response and community mobility. We also noted the substantial variation in the number of Covid-19 cases and the government and community response to the pandemic across the U.S. states. In this section, we use state-level data on government stringency and community mobility indices to understand how much they contributed to the containment of the pandemic at the state-level. First, we use the panel fixed-effect regressions to estimate common quasi-elasticity of the growth rate of new cases of Covid-19 w.r.t. changes in the government stringency index and community mobility indicators response across states and over time (see subsection 3.3.1). Second, we use OLS regressions to estimate quasi-elasticity estimates for each state separately (subsection 3.3.2). Here, we show that not only had the states with Republican governors followed less stringent policies in response to Covid-19 but also, as a result of these policies, they ended suffering from faster growth of new Covid-19 cases. Finally, in this section, we show that the politicization of the whole pandemic response process is observed when one compares the states in terms of the community mobility indicators and travel intensity measures (mobile phone location) as well.

3.3.1 The Government & Community Response Matters

Both the government stringency index and the CMIs are likely to be subject to the endogeneity problem. As the number of cases starts to follow an upward trend, the state governments would be under pressure to take more serious public health policy measures. Similarly, local communities will be restricting their public space use in reaction to the increased growth momentum of the virus. Taking this fact into account, we correct for the possible simultaneity of all the right-hand side variables, using residuals from a regression on lags of the 7-day moving average of the growth rate of new cases. Then, we regress the 7-day average new case growth rate on the residuals and its own lags.

Fixed-effect regression results in Table 1 show that policy stringency is effective in lowering the 7-day average growth rate of new confirmed cases. As the number of lags

of the policy variable is increased from one to 4 and 7 days, the elasticity of the growth rate w.r.t. to the policy stringency increases in absolute value from -0.005 to -0.026 and -0.051, respectively. The lagged policy effect on the new cases' growth rate increases further to -0.105 at 14 days before declining to -0.083 with a 21-day lag. The 14-day coefficient estimate implies that a ten % increase in the policy stringency index generates as high as a 1.0 percentage point drop in the growth rate of new Covid-19 cases (7-day average) within two weeks. This points to a significant impact on public health policy measures. The lagged growth rate coefficients are positive and statistically significant; as the number of lags is increased from one-day to 21-days, the coefficient estimate of the lagged growth rate declines monotonically from 0.911 to 0.021, and eventually becomes statistically insignificant.

Variables \ Lags	1 day	4 days	7 days	14 days	21 days
Stringency Index	-0.005** (0.001)	-0.026** (0.003)	-0.051** (0.004)	-0.105** (0.007)	-0.083** (0.005)
Lagged Growth Rate	0.911** (0.006)	0.670** (0.017)	0.433** (0.026)	0.194** (0.019)	0.0207 (0.018)
Adjusted R^2	0.832	0.475	0.279	0.308	0.442
Observations	11,952	11,809	11,668	11,519	11,319
Avg. CMI4	0.044** (0.006)	0.168** (0.021)	0.220** (0.026)	0.222** (0.022)	0.137** (0.014)
Lagged Growth Rate	0.912** (0.005)	0.677** (0.017)	0.453** (0.026)	0.240** (0.020)	0.060** (0.017)
Adjusted R^2	0.831	0.484	0.286	0.226	0.090
Observations	11,399	11,348	11,195	10,838	10,481
Residential Places	-0.110** (0.011)	-0.457** (0.041)	-0.603** (0.053)	-0.614** (0.045)	-0.403** (0.030)
Lagged Growth Rate	0.914** (0.006)	0.686** (0.018)	0.464** (0.027)	0.254** (0.019)	0.068** (0.017)
Adjusted R^2	0.831	0.491	0.300	0.257	0.121
Observations	11,475	11,424	11,271	10,914	10,557
Robust standard errors in parentheses; ** p<0.01, * p<0.05, + p<0.1					

Table 1: Panel Regressions – Growth Rate of New Confirmed Covid-19 Cases on Policy Stringency and Community Mobility Measures (We corrected right-hand side variables for potential endogeneity by regressing them on the 7-day lagged new confirmed cases).

As the regression results suggested, strict public policy implementation is crucial for containing the virus. When used in a separate regression, the changes in community mobility patterns are also critical in the containment of the Covid-19 pandemic. Even though community mobility can be influenced by strict public policy measures, such as nationwide or regional lockdowns, it also depends on the public awareness of the risks involved and the desire to act to save lives.

As more stringent policies are likely to restrict community mobility as well, it is not feasible to put both stringency and community mobility measures together in a regression.

When we use the average of the four alternative community mobility indices⁴ (Avg.CMI4) published by Google, its coefficient estimate increases from 0.044 with a one-day lag to 0.222 with a 14-day lag before decreasing to 0.137 with a 21-day lag. A 10% increase in Avg.CMI4 variable lowers the Covid-19 growth rate by up to 2.22 percentage points.

An alternative to the Avg.CMI4 variable that can be used in the regressions is the residential space variable; it measures the intensity with which the residential space is used relative to its use in the reference period (namely the whole month of January and the first week of February). As the residential space use increases, each of the four mobility measures (summarized by the Avg.CMI4) decreases. The increased residential use turns out to be more effective in lowering the growth momentum of the daily new Covid-19 cases: Its coefficient estimates vary from -0.11 with a one-day lag to -0.614 with a lag of 14 days before declining (in absolute value) to -0.403 with a 21-day lag.

According to the estimated coefficients, the increase in residential space use appears to be more effective compared to Avg.CMI4 (as an average of four other CMI measures) in lowering the growth momentum of the Covid-19 pandemic. The difference in coefficient estimates is in part due to the fact that the residential space use fluctuated by much less compared to other CMIs. While the residential space use increased to 19.5% above the reference period, the Avg.CMI4 declined by as much 41.4% compared to the reference period.

3.3.2 Response and Performance Varies Along the Party Lines

The findings of the panel regressions on the growth of new cases (see Table 1) show that strict public health policies and reduction in public space utilization by the communities would lower the growth momentum of the Covid-19. In this section, we shift our attention to investigate the government and community response, and the resulting Covid-19 cases vary along the party lines.

We first show that the growth momentum of the Covid-19 pandemic is much stronger among the states with Republican governors. Figure 3 presents the daily average number of new cases per capita (7-day MA) when states are grouped on the basis of the governor's party affiliation. While the number of new cases per capita in March through the end of May was much higher in the states with Democratic governors, states with Republican governors outstripped their Democratic counterparts as of the first week of June. Since

⁴ In fact, there is the fifth measure of community mobility; the use of parks, which we do not include in the calculation of the Avg.CMI4 variable because even during the lockdowns in some states, people were allowed to use parks observing social distance rules. Consequently, while all other community mobility measures may decline, reflecting the effect of containment measures, the data of the use of parks may increase. Indeed, the coefficient estimate of the social space use in parks (which we do not report here to save space) is negative and statistically significant.

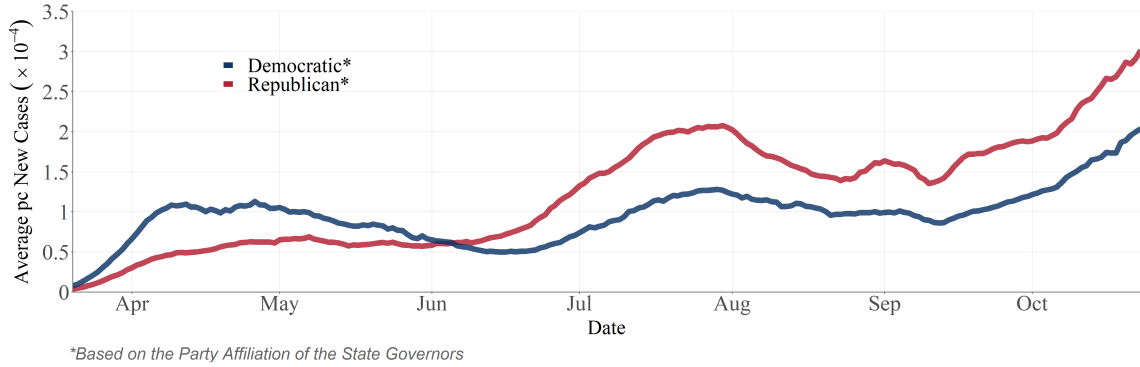


Figure 3: Average Number of New Cases Per Capita (7-day MA) – States Grouped on the basis of the Party Affiliation of the Governor

then, the number of new cases per capita in states with Republican governors has been 30-40 percent higher than the corresponding number for the states with Democratic governors.

We can also have a closer look at the performance of each state in terms of the policy stringency throughout the sample period. Figure 4 plots the stringency of the state government policies to contain the coronavirus pandemic. States are ordered on the basis of the difference of the state’s sample-period average stringency index from the cross-section average over all 51 states in the March-October period (from the highest to the lowest). It is clear from the plot that the states with Democratic governors (blue-colored bars) overwhelmingly followed more stringent policies to contain the virus, whereas the states with Republican governors (red-colored bars) overwhelmingly followed less stringent policies.

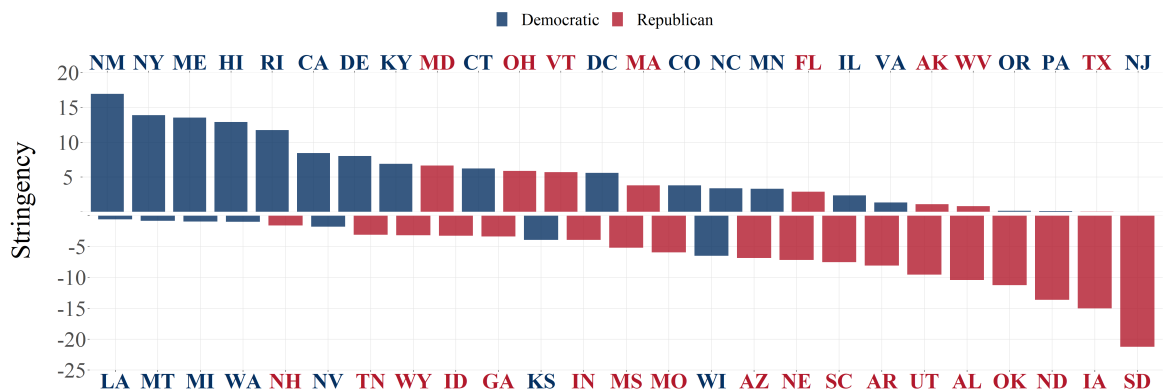


Figure 4: State Government Response to Coronavirus Pandemic - Difference from the 51 State Average, of the Average Stringency Index in the March 12-October 23 period.

Differences in state government policy stringency are likely to lead to differences in the growth rate of Covid-19 cases across the states. In order to understand this relationship better, we repeat the regressions of the new case growth rates (7-day average) on its lags

and the lagged government stringency index for each state separately. This provides us with a different estimate of the quasi-elasticity for each state. Then we multiply the estimated quasi-elasticity of each state with the difference between the state’s average government stringency index and the average government stringency index for all 51 states over the sample period.

The resulting growth rate is the implied growth rate of new Covid-19 cases due to state governments following public policy measures that have been less/more stringent than the average of all 51 states. We plot the implied average daily growth rates for each state in Figure 5.

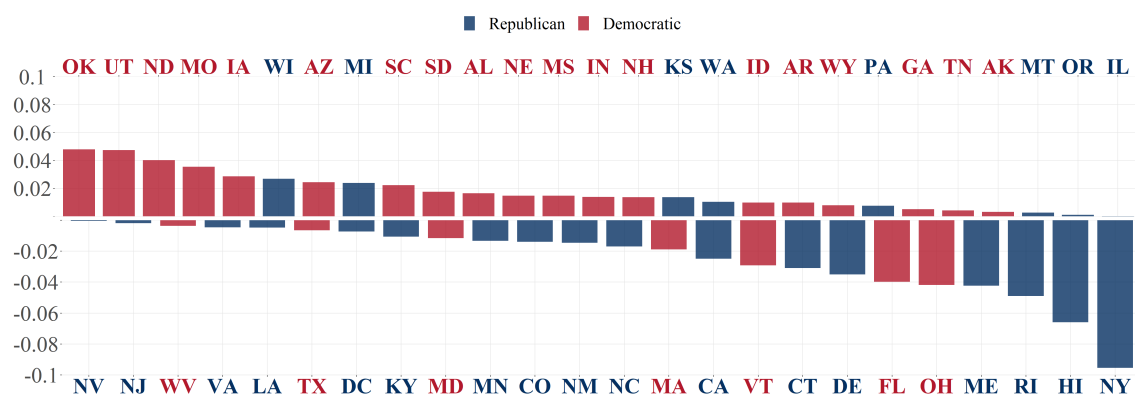


Figure 5: State Government Policy and the Implied New Case Growth Impact Estimates (based on regressions with 14-day lags) The state’s actual average daily new Covid-19 case growth is X percentage points lower/higher than it would have achieved had it followed a policy response equivalent to the 51-state average stringency index over the full sample.

Each state’s implied average daily new cases growth over the March 12-October 23 period is higher/lower than what would have otherwise been had the state implemented policies equivalent to the 51-state average stringency level. To make this more concrete, let us take Oklahoma as an example. Oklahoma’s estimated quasi elasticity vis-a-vis the stringency index is -0.108. Its average stringency index for the sample period is 35.78, whereas the average value of average stringency indices of all states is 55.8. Oklahoma’s policy restrictiveness was 20 points lower than the average for all states over the sample period. As a result, Oklahoma’s average new cases’ growth rate ends up being 4.8 percentage points higher than it would have been the case if it followed stricter policies to attain the median stringency index level.

In the other extreme, New York was able to lower its Covid-19 new case growth rate by almost 9.5 percentage points thanks to following very strict public health policy (with a period average stringency index of 76, 21.5 points higher than the median value for all 51 states) in the six months from March 12 to October 23.⁵

⁵ We are aware of the relatively high value of the implied growth impact estimates of the state-level

When we rank the states in terms of the success in controlling the growth rate of the new infections of the Covid-19 virus, 7 of the top 10 performers have a Democratic governor, whereas only three have Republican governors. Two of these states are Florida and Ohio that are considered as the battleground states during the 2020 Presidential elections, and the other one is Vermont. In contrast, eight of the bottom-ten performers have a Republican governor, and only two have a Democratic governor. The picture does not change when we look into the top 20 and bottom 20 performers in terms of the reigning in the growth rate of the cases of Covid-19 virus: 14 of the top 20 performing states have Democratic governors, where 16 of the bottom 20 performing states have Republican governors.

As a consequence of the substantial differences in policy response, states with Democratic governors were able to contain the spread of the virus better than the median, as measured by the difference of each state's (period average) growth rate of the new Covid-19 cases from the median growth rate over 51 states. In contrast, mostly the states with Republican governors that followed rather lax public health policies ended up suffering from faster growth of new cases of the virus in their jurisdictions (see Figure 5).

Having shown the differences between states with Democratic and Republican governors in terms of the public health policy implementation (or community mobility patterns) and the growth momentum of new Covid-19 cases over the full sample, we now focus on the behavior of daily average policy stringency index and community mobility measures for the states with Democratic and Republican governors.

Figure 6 shows the behavior of the average policy stringency index in the states with Democratic and Republican governors. From the beginning on, states with Democratic governors responded faster than the states with Republican governors to the Covid-19 virus by undertaking stricter public policy measures to contain the virus. The average stringency index for the states with Democratic governors reached as high 75 in mid-April, while that of the states with Republican governors reached 68. After the end of April, both groups of states relaxed the public health measures, gradually dropping their respective indices to respective values of 60 and 45 in mid-June and to 50 and 36 as of October 23, 2020.

We also need to pay closer attention to the difference between the two groups. The difference between the two groups increased to 12 points (out of a maximum of 100) by the end of March. As the states with Republican governors started to suffer from increased numbers of Covid-19 cases in April, they started to undertake stricter measures in the stringency indices. We nevertheless present these results to show how much the policy differences play into the estimated growth effects across states.

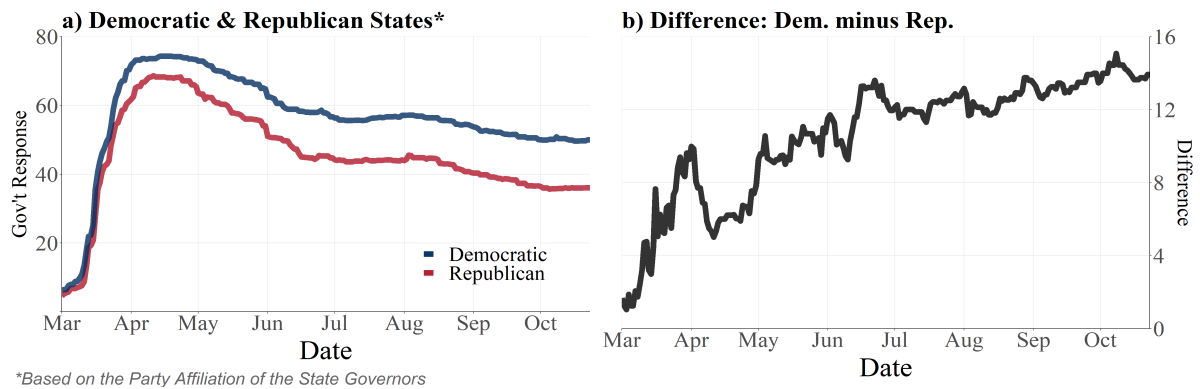


Figure 6: Government Response Over Time – States with Democratic vs. Republican Governors

rest of the month, dropping the difference to as low as 6 points. Starting in May, however, the difference increased further to reach 14 points by June 20 and fluctuated between 12 and 14 points since then.

The comparison of the average mobility index (Avg.CMI4) for the two groups of states in Figure 7 depicts a similar picture as we obtained from the comparison of policy stringency index in Figure 6.⁶ Communities in states with Democratic governors, on average, spent as much as 40% less time in public spaces compared to the level they had in the comparison period. The communities in the states with Republican governors, on the other hand, reduced their public space use by as much as 33% in mid-April relative to the level in the comparison period. From the beginning of July to October 23, the states with Democratic governors reduced their public space use by 7.5-9 percentage points more relative to the states with Republican governors.

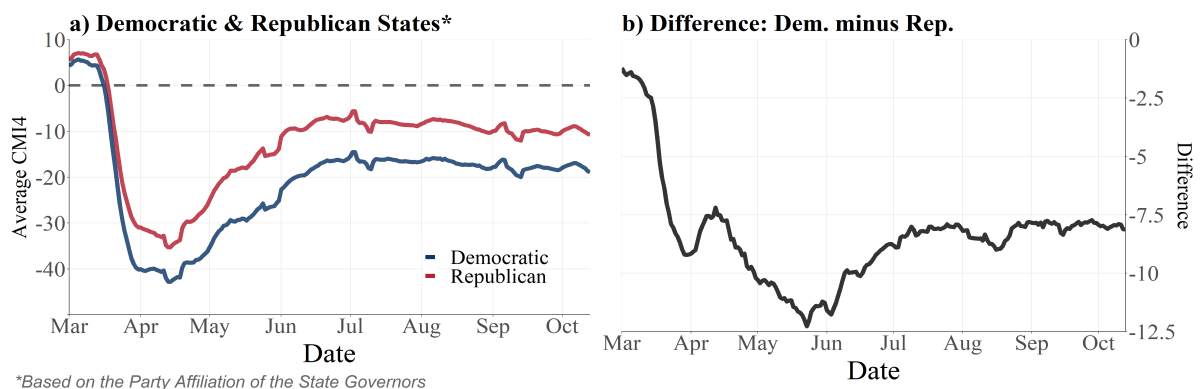


Figure 7: Avg.CMI4 Over Time – States with Democratic vs. Republican Governors

Both the government stringency index and the community mobility indicators provide us with the government and community response within each state. Neither of the two

⁶ Avg.CMI4 is the average of the four public space use measures excluding the use of parks.

measures provides any information about the links between states that would help the virus spread across states. The channels through which the virus is spread across the states is very closely related to the intensity of travel between states from the beginning of the pandemic and whether there are any differences of travel intensity between and within groups of the states with Republican and Democratic governors. Towards that end, we aggregate the mobile phone location exposure (LEX) data between states to obtain the directional travel intensities within and between the states with Republican and Democratic governors (based on the party affiliation of the governor), presented in Figure 8.

The traveling among the states with Democratic governors declined by as much as 60% as of April 19 (relative to the comparison period of January and the first week of February), while traveling among the states with Republican governors declined by 50% at the most around the same day. In both groups of states, traveling intensity among the states with Republican governors increased gradually over time to reach levels higher than the reference period in July and August. A similar tendency is observed in the intensity of travelling among states with Democratic governors, but it reached only to 90% of the level in the reference period.

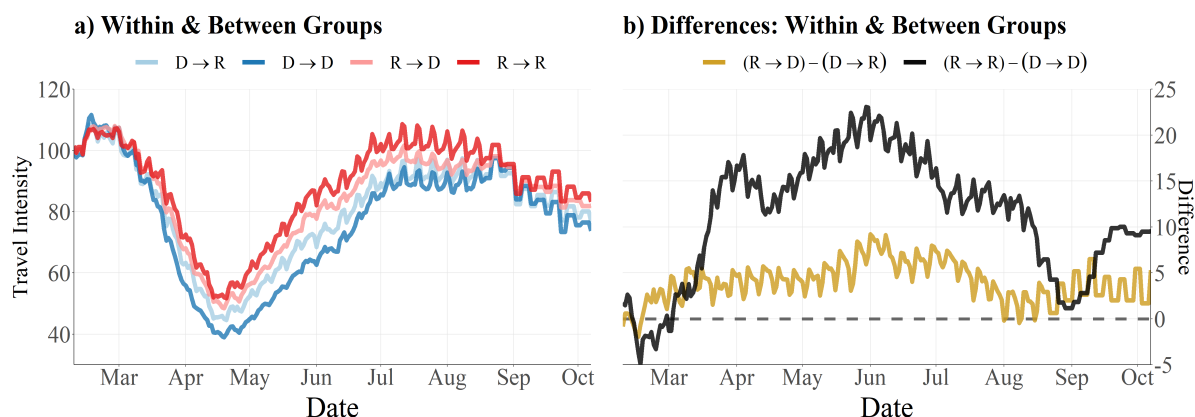


Figure 8: Location Exposure Index Over Time – States with Democratic vs. Republican Governors

Interestingly, from early March onwards, the difference between the travel intensity within the groups of the states with Republican and Democratic governors increased and reached to 15% by the last week of March. After a brief hiatus in the first half of April, the difference between the two groups started to increase again to reach as high as 22% by the end of May. The difference declined in the course of the summer vacations and fall to below 5% at the end of August, before increasing again to 10% as of the end of September. To summarize, the within-group LEX measure indicates that the states with Republican governors restricted travel by much less than the states with Democratic

governors.

When we look at the intensity of travel between the states with Republican and Democratic governors, the between-group travel intensities follow a time-series pattern similar to that of the within-group travel intensities (See Figure 8(a)). Yet, the intensity of travel from the states with Republican governors to the ones with Democratic governors appears to be higher than the intensity of travel from the the states with Democratic governors to the ones with Republican governors during the pandemic (yellow line in Figure 8(b)).

4 Covid-19 Connectedness Across States

In the previous section, we showed that states with Democratic governors implemented more stringent public health policies at the state level, compared to the Republican governors. Based on the state-level average policy stringency index multiplied by the estimated average policy impact coefficient, we showed that the growth rate of new Covid-19 cases could be lower in the states with Republican governors if they had followed stricter policies. We repeated the same exercise with the community mobility indicators, and a similar result applies in that case as well. In this section, we shift our focus to the analysis of the regional connectedness dynamics of Covid-19.

4.1 Connectedness Framework

Our empirical approach builds on the Diebold-Yilmaz connectedness methodology, which was developed in a series of papers (Diebold and Yilmaz (2009, 2012, 2014)).

The connectedness approach starts with a covariance stationary N -variable vector autoregression (VAR(p)), $x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon \sim (0, \Sigma)$.

The moving average representation of VAR(p) is given by $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N \times N$, coefficient matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$, with A_0 an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$.

The coefficients of the MA representation (or its transformations such as impulse response functions or variance decompositions) are critical for understanding the dynamics of the VAR system. Diebold-Yilmaz connectedness approach uses the variance decompositions, which splits the forecast error variances of each variable into parts attributable to the various system shocks. Variance decompositions also allow one to assess the fraction of the H -step-ahead error variance in forecasting x_i that is due to shocks to $x_j, \forall i \neq j$, for each i .

A study of the connectedness of Covid-19 across the states of the U.S. requires one

to obtain the pairwise directional connectedness measures. Calculation of variance decompositions requires orthogonal innovations, whereas the VAR innovations are generally correlated. Identification schemes such as that based on Cholesky factorization achieve orthogonality. However, the resulting variance decompositions then depend on the ordering of variables, making it impossible to use them to study directional connectedness. With this understanding, Diebold and Yilmaz (2012) proposed to circumvent this problem by exploiting the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), which produces variance decompositions invariant to ordering.

Instead of attempting to orthogonalize shocks, the generalized approach allows correlated shocks but accounts for them appropriately using the historically observed distribution of the errors. As the shocks to each variable are not orthogonal, the sum of contributions to the forecast error variance (that is, the row sum of the elements of the variance decomposition table) is not necessarily equal to one.

The generalized impulse response and variance decomposition analyses also rely on the MA representation of the N -variable VAR(p) equation above. Pesaran and Shin (1998) show that when the error term ε_t has a multivariate normal distribution, the h -step generalized impulse response function scaled by the variance of the variable is given by:

$$\gamma_j^g(h) = \frac{1}{\sqrt{\sigma_{jj}}} A_h \Sigma \mathbf{e}_j, \quad h = 0, 1, 2, \dots \quad (1)$$

where Σ is the variance matrix for the error vector ε , σ_{jj} is the standard deviation of the error term for the j^{th} equation and \mathbf{e}_i is the selection vector with one as the i^{th} element and zeros otherwise.

Variable j 's contribution to variable i 's H -step-ahead generalized forecast error variance, $\theta_{ij}^g(H)$, for $H = 1, 2, \dots$, is defined as:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \quad (2)$$

As explained above, the sum of the elements of each row of the variance decomposition table is not necessarily equal to 1: $\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$.

To use the information available in the variance decomposition matrix to calculate the connectedness index, Diebold and Yilmaz (2012) normalizes each entry of the variance decomposition matrix by the row sum. While normalized off-diagonal entries of the generalized variance decomposition matrix measure the pairwise directional connectedness between pairs of variables in the system, their column-sum and row-sum give the 'to' and 'from' directional connectedness measures between them. Finally, the

sum of all off-diagonal entries of the generalized variance decomposition matrix is a measure of the system-wide or total connectedness of the variables.

Once we obtain the connectedness measures, we plot the system-wide connectedness index for the US, analyze its behavior over time, and relate it to the government and community response to the pandemic at the state level. Then we move to the regression analysis of the pairwise regional connectedness measures.

After showing the close association between government and community response to the pandemic and the growth momentum of infections at the state-level, we now shift our focus to the possibility of spillovers of infections across states. In particular, it is of great interest to understand whether the states with higher and rapidly growing infections spread the virus to neighboring and distant states through road and air travel, which have not been restricted in the United States since the beginning of the Covid-19 pandemic. Similar to the logic at the individual level, some states implementing strict public health policy measures, communities restricting their daily movements would not be as fully effective in controlling the disease because it is possible that other states and their communities do not follow similarly responsible policies and behavior can transmit the virus to the others.

4.2 Dynamic System-wide and Directional Connectedness

In Figure 9, we present the connectedness index across 51 states obtained from 56-day rolling window estimations of a VAR(3) of the weekly growth rates of (7-day average) daily new Covid-19 cases. Along with the index, we plot the three-days moving average of it.

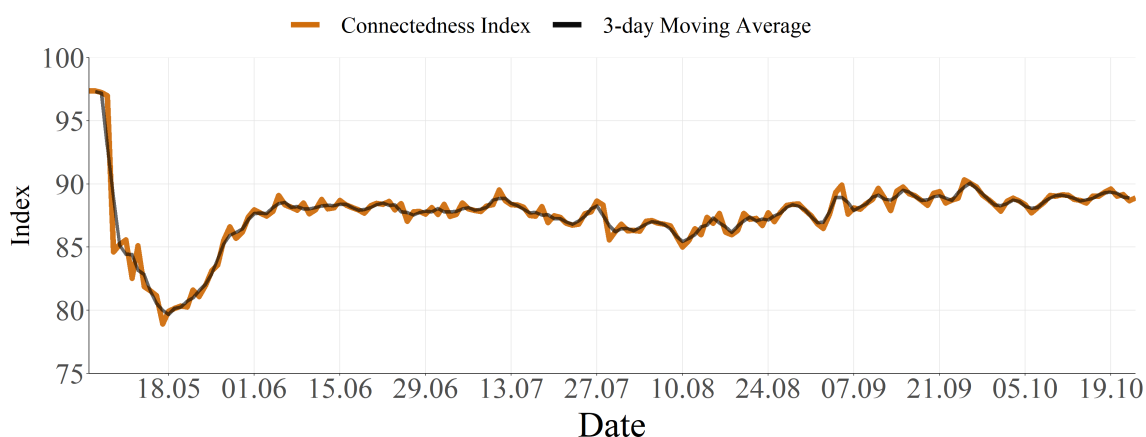


Figure 9: Dynamic System-wide Covid-19 Connectedness

As our sample starts on March 8, the connectedness measures for the first rolling

window is obtained as of May 5. The fact that early on, new Covid-19 cases in especially Western and Eastern coastal states increased and spread rather fast, the connectedness index starts at 96.1. As the window is rolled over, the index drops to 80 within ten days and fluctuates between 80 and 85 percent until the Memorial Day holiday weekend at the end of May. With the easing of restrictions at the state and federal level in late May and increased intensity of travel and community mobility during the Memorial Day holiday, the connectedness index quickly moves to 88 percent and fluctuates around that level in June and July. Once the observations for late May and early June are dropped from the sample window as the window is rolled further, the index drops to 84 and gradually increased afterward. It reaches a local peak of 92 in mid-September and fluctuates 88 and 90 until the end of the sample.

In the previous section, we showed that states with Republican governors had implemented less stringent policies than the states with Democratic governors. As a result, they experienced higher daily growth rates of new Covid-19 infections than states with Democratic governors, and new Covid-19 cases per capita in the states with Republican governors were higher than the states with Democratic governors since the beginning of June. Having calculated the directional connectedness measures, now we have a closer look at whether a clear pattern emerges in the net directional connectedness between the states with Republican and Democratic governors.

The net directional connectedness measures in Figure 10 fluctuate substantially over time. Yet, starting in mid-May, we can detect a clear pattern of net connectedness of Covid-19 cases from the states with Republican governors to the to the ones with Democratic governors.

In the first two weeks of rolling sample windows (05/05–05/10), we observe that the connectedness from the states with Democratic governors to the ones with Republican governors was rather high, 2.5 points, compared to the connectedness from the states with Republican governors to the ones with Democratic governors, 1.51 points (see Figure 10a), implying a net connectedness of around -1.0 points between the two (see Figure 10(b)).

When considered together with the system-wide connectedness plot in Figure 9, it is clear that from early March to the first week of May, the states with Democratic governors contributed substantially to the system-wide connectedness. Within two weeks, the net connectedness of the states with Democratic governors to the states with Republican governors declined and eventually fell below zero (Figure 10).

This result is fully consistent with what we know: The Western Pacific and North-Eastern Atlantic states, many of which are governed by Democratic governors, received the virus from abroad (both Europe and Asia) in early March before the landlocked states that are mostly Republican. These states implemented very strict measures to contain

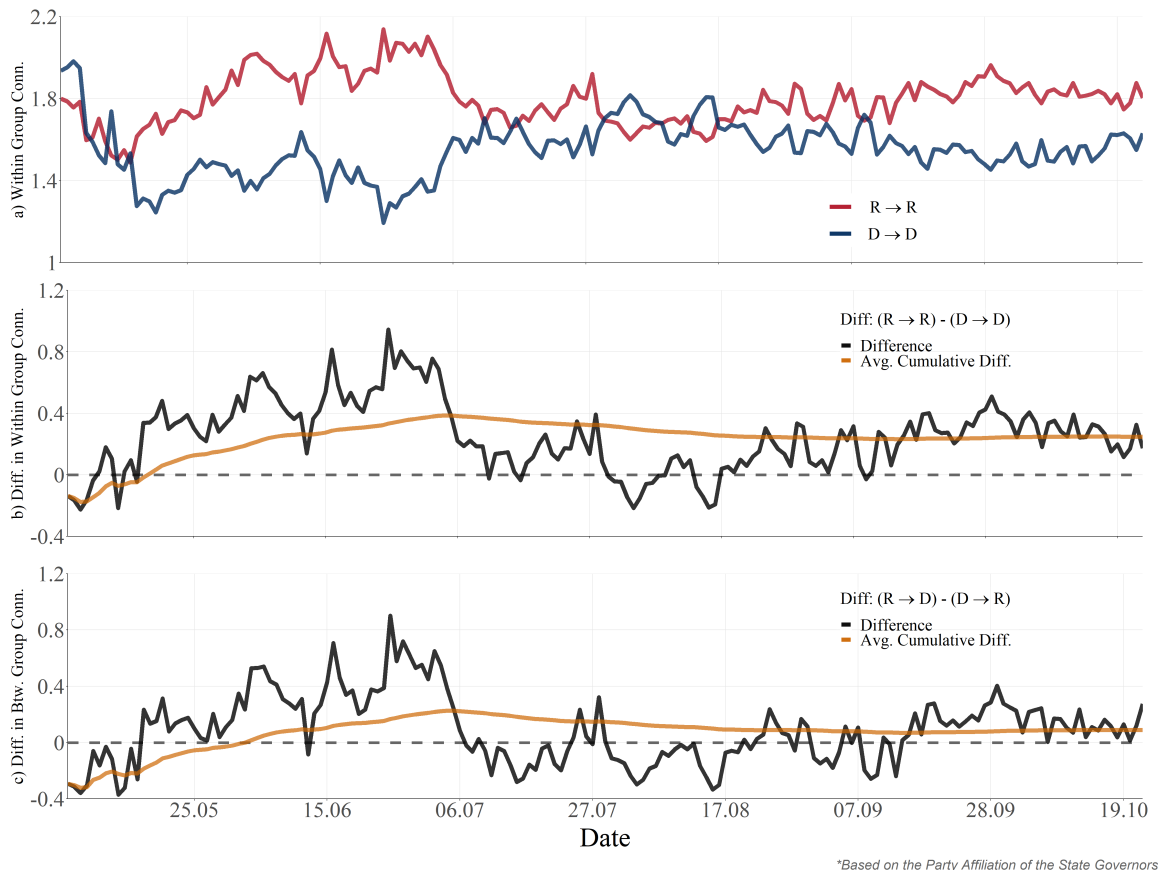


Figure 10: Directional Connectedness Within and Between Groups – States with Democratic vs. Republican Governors

the virus and succeeded in flattening the curve (that is, lowering the growth rate of new Covid-19 cases, while at the same lowering the connectedness to other states.

Faced with a rapid increase in the number of cases in a very short period of time, the Democratic state governments realized the gravity of the situation and implemented stringent public policy measures to contain the virus. Republican state governments, on the other hand, did not display a strong policy response to the pandemic threat. In the absence of active policy response from state governments, the majority of the states with Republican governors started experiencing an increasing number of infections. From mid-May onwards, the states with Republican governors started generating positive net directional connectedness to the the states with Democratic governors. The size of net connectedness that ranged between 0 and 0.4 points in the first week of June moved up to the 0.4-0.8 points range in the second half of June and the first week of July.

As a result of the pandemic and the strict policy measures, the United States, like many other countries around the world, suffered substantial human losses and economic costs. The governments were under severe pressure to start opening up businesses, especially the service sectors. Millions of families who were effectively locked in their

own homes for several months looked for ways to get out and go back to normal. Even states with Democratic governors relaxed their public health policies as the new infections lost momentum in the second half of May, along with the increasing daily temperatures.

We have already seen in Figures 6 and 7 that as the government policies were relaxed in late May, the travel restrictions were lifted in both groups of states. However, the relaxed state government policy, as well as the increased community mobility, prepared the ground for further infections in the summer (see Figure 3) and increased connectedness of the virus across the states.

The connectedness from the states with Republican governors to the ones with Democratic governors declined in July and August compared to the months of May and June (see Figure 10(a)). Despite the fluctuations, net connectedness from the states with Republican governors to the ones with Democratic governors stayed on the positive side for most of the period since August. Figure 10(b) shows that the cumulative daily average net connectedness from the states with Republican governors to the ones with Democratic governors (represented by the yellow line) stayed since early June.

The difference between the within-group net connectedness, which we plot in Figure 10(c), follows a time-series pattern similar to the between-group net connectedness. But it is always higher than the between-group net connectedness. While the average cumulative between-group net connectedness stabilizes around 0.09, where the average cumulative within-group connectedness stabilizes around 0.25 (as represented by the solid yellow lines in Figure 10(b) and 10(c), respectively). The within-group connectedness patterns also support the results we obtained from the between-group net connectedness patterns over time: Lax government and community response in the states with Republican governors not only led to higher growth rates of Covid-19 cases in each of these states but also generated connectedness of the Covid-19 cases to other states, more so to other states with Republican governors.

5 Covid-19 Connectedness & Secondary Regressions

So far, we have analyzed the dynamic behavior of Covid-19 cases and its connectedness across the U.S. states and provided some evidence that the states with Republican governors tend to generate Covid-19 connectedness to each other as well as the states with Democratic governors. This analysis, however, could not help us identify the factors that contribute to the pairwise connectedness of cases across states. In this section, we undertake secondary times series and panel regressions to understand the relationship between the system-wide connectedness and the number of new cases at the

national level and identify the factors that possibly drive pairwise connectedness across states, including the party affiliation of the governor.

5.1 Impulse Response Analysis of Cases and Connectedness

Having discussed the dynamic behavior of the connectedness measures, we think the index by itself carries important information to gauge the momentum of newly reported infections. To understand how a shock to system-wide connectedness affects the new infections in the country, *ceteris paribus*, we apply impulse-response analysis on the 7-day growth rates of the (7-day average) new confirmed cases and the connectedness index. Figure 11 illustrates the responses of new infections to the connectedness shocks along the forecast horizon. The figure also includes the results from VAR models with different lag structures up to 3-days lagging while the results of VAR(1) models are emphasized. Moreover, we prefer to stay silent about the orderings of the variables to achieve identification of the VAR system, as models with alternative orderings do not affect the validity of our argument: the positive shocks to the system-wide connectedness lead to an increase in the number of new infections at the national level.

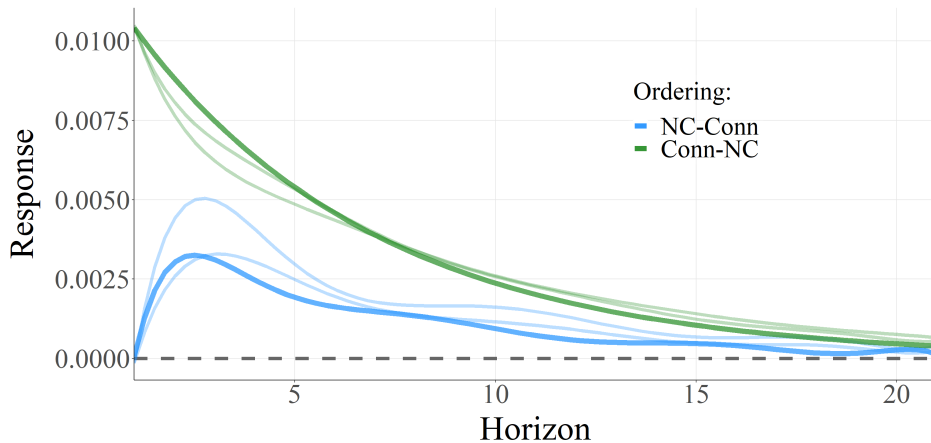


Figure 11: The Response of New Cases (7-day average) to Connectedness Shocks

The intuition behind that result is not trivial. As seen in the following sections, a change in Covid-19 growth connectedness among regions is significantly associated with the conditions that facilitate the spread across states. Not surprisingly, restrictions on community mobility and widespread adoption of protective measures keep both the number of new cases and its connectedness across states under control. When the strict public health policy measures are relaxed, we are likely to observe the connectedness outcome surge along with an increasing number of infections. The analysis also points out the presence of a circular relationship where the positive feedback from the regional

connectedness allows the number of new cases to grow further. This result is essentially important from a policy-making perspective. Since the beginning of the Covid-19 outbreak, many researchers and public health officials repeatedly put particular emphasis on “flattening the curve” (FTC) policies against the “herd-immunity” approach to keep the daily new cases at a manageable level regarding the limited medical capacity of health institutions. Our result yields a further implication that “flattening the connectedness curve” (FTCC) at the national level also matters to support the conventional FTC approach. Along with other measures, FTCC implies that the fight against the growing pandemic may require a more active policy stance at the federal government level that would directly reduce the connectedness across states.

Armed with the result that information embedded in the system-wide connectedness can be a useful indicator for the future course of Covid-19 cases, our next task is to measure the impact of government stringency and community mobility on the pairwise Covid-19 growth connectedness outcomes. Instead of estimating secondary regressions on aggregate measures such as system-wide index, to- and from-connectedness, and other aggregate measures, we prefer to utilize a more granular approach and focus on the pairwise measures connectedness. In pairwise secondary regressions, we use variables that gauge the potential for connectedness among pairs of states as well as variables that capture state characteristics that can be of importance for the spread of the virus.

5.2 Panel Regressions Analysis of Pairwise Connectedness

In order to identify factors that contribute to pairwise connectedness across the U.S. states, we estimate panel data regressions of the following form over the full sample (from May 5 through October 23, 2020):

$$\tilde{\theta}_{ij,t}^g = \beta_0 + \beta X_{ij,t} + \alpha_j + \gamma_i + \tau_t + u_{ij,t} \quad (3)$$

where

- $\tilde{\theta}_{ij,t}^g$: daily directional pairwise connectedness from state j to state i
- $X_{ij,t}$ denotes a set of regressors that include
 - Government policy stringency index (GSI) in state j relative to state i
 - Community mobility measures (CMI) in state j relative to state i
 - State-level location exposure index (LEX): Among the smartphones that pinged in state i on a given day, the share that pinged in state j at least once in the previous 14 days.

- γ_j , α_i and τ_t are the source, target and time fixed-effects, respectively.

Let us start the discussion of the variables with the ratios of community mobility indicators (CMI) for the source and target states. CMIs are crucial to understanding the difference in the community preference on the public space use across regions. Except for the use of residential places (*Resdnt*) indicator, we expect that an increase in the source to target state ratios of all CMIs to have a positive impact on pairwise regional Covid-19 connectedness. The higher the mobility in the source state relative to the target state, the more likely would it be for the source state to have a higher number of Covid-19 cases. Then we would expect it to be more likely to have the virus transmission take place from the source to the target state, rather than the other way around. Wilson (2020) shows the dynamic response of Covid-19 cases to different mobility measures, including CMI and device exposures, and argues that mobility increases the number of new cases in 3-10 weeks and deaths in 8-10 weeks significantly. Wang and Yamamoto (2020) attempt to forecast the new Covid-19 cases in regions of Arizona and verify the positive short-term effect of precautionary measures on the spread of Covid-19 using the Google mobility indices.

Next, we include the ratios of public policy stringency index in distinct pairs of states to see whether the differences in public policy have anything to do with the spread of the virus across states. As we have already highlighted above, the stringency index was one of the factors that slowed down the rate of growth of the number of new Covid-19 cases. Therefore, it is legitimate to incorporate it in the pairwise connectedness regressions as well.

It is also crucial to note that community mobility and stringency measures are not necessarily exogenous to the increase in the number of Covid-19 cases. As the Covid-19 cases in a region increases, the local government or the members of the local community themselves may introduce restrictions to diminish mobility outside of residences. As a result, the community mobility measures we intend to use as RHS variables in the secondary regressions can be endogenous to changes in the number of new Covid-19 cases.

Taking this possibility into account, we first apply state-level regressions for each of the community mobility indicators on the 7-day MA new cases. Then, we use the resulting residual term as the community mobility and stringency measures, which are assumed to be orthogonal to the number of new cases and can be used as a right-hand-side variable in the secondary regressions described above.

In addition, we would like to have a variable that provides us with information on the intensity of travel from the source to the target state. After all, individual mobility is the only way for the virus to spread across states. We don't have data that directly measures

travel intensity between states. Instead, we use the publically available mobile phone location exposure (LEX) data for the U.S. states, which is collected by PlaceIQ. Couture et al. (2020) similarly emphasize that the index can be used as a proxy for individual mobility.⁷

To be more specific, the variable LEX measures the share of mobile phones that are pinged in the target state j on a specific day were also pinged on the source state i within the previous 14 days. This is a variable that is more valuable for the secondary regressions because it varies from one day to another. Furthermore, unlike the ratios of variables in pairs of distinct states, it is truly pairwise and directional. It measures the tendency of mobile phones and hence persons to travel from the source to the target state.

All three RHS variables, LEX, CMIs, and GSI, vary both across pairs of states and over time, allowing us to capture their possible effects on pairwise connectedness. We present the secondary regression results in Table 2. In secondary regressions, we use 438,600 observations over time, and across 51 states.⁸ Adjusted R^2 varies between 0.024 and 0.028 for all eight sets of regressions.⁹ It is not unusual to obtain very low values of the goodness of fit. The dependent variable, as well as the RHS variables, are obtained for pairs of states, and statistically significant coefficient estimates are of key importance to establish the relationship between the RHS variables and the measures of pairwise connectedness.

All independent variables are in logs. The dependent variable, that is, the pairwise connectedness measure, is in levels and theoretically can vary between 0 and 100.¹⁰

Column (1) presents the coefficient estimates for the location exposure index (LEX) between the source and target states, as well as the ratios of the state government policy stringency indices in the source and target states, all lagged for one, 4, 7, 14 and 21 days.

Column (2) through (8) of Table 2 presents the coefficient estimates for the variables of Column (1) when they are included in the regressions along with the six community mobility indicators and *AvgCMI*, included in the regressions one at a time.

In Column (1), the LEX coefficient estimates (in the middle panel) show that the pairwise Covid-19 connectedness between the source and target states is directly related

⁷ Huang (2020) uses smartphone data and reports that social distancing measures based on mobility indicators reduce the average daily infection cases by %12. Brinkman et al. (2020) utilize LEX data to document spatial mobility changes during the early phase of the Covid-19 outbreak and show a significant drop in county-level mobility. Weill et al. (2020) use the alternative indices using the mobile phone location data, which is also distributed by *PlaceIQ*, the “device exposure index” to analyze the mobility within specific venues.

⁸ As we use daily data for 51 states, there are 2550 observations of state pairs for each day.

⁹ We report the adjusted R^2 's for regressions with one-day lagged RHS variables with. The adjusted R^2 's for 4- to 21-day lagged regressions are very close to the ones reported in Table2.

¹⁰ The maximum value of the pairwise connectedness measures out of 438,600 observations is 30.417. Ninety-nine percent of all pairwise connectedness measures fall below 5.46.

		<i>Dependent Variable: Pairwise Connectedness</i>							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Community Mobility Measures included as RHS Variables – One at a Time</i>									
			<i>RetRec</i>	<i>GroPhar</i>	<i>Parks</i>	<i>TraSta</i>	<i>WorkP</i>	<i>Resdnt</i>	<i>AvgCMI</i>
<i>Lagged: 1-day</i>	–	-3.858 (2.412)	-2.363 (3.913)	-1.594** (0.430)	-0.620 (2.130)	-16.966** (5.062)	54.865** (7.672)	-4.588 (3.302)	
<i>4-day</i>	–	6.398** (2.469)	7.896* (3.943)	-1.816** (0.442)	9.716** (2.192)	15.355** (5.230)	9.914 (8.022)	13.538** (3.400)	
<i>7-day</i>	–	15.998** (2.514)	17.511** (3.991)	-1.221** (0.436)	16.458** (2.219)	36.339** (5.373)	-24.832** (8.299)	25.480** (3.475)	
<i>14-day</i>	–	28.877** (2.516)	14.977** (3.962)	-3.391** (0.412)	16.967** (2.217)	49.797** (5.302)	-63.066** (8.471)	30.825** (3.479)	
<i>21-day</i>	–	29.121** (2.414)	18.803** (3.774)	-4.808** (0.395)	12.706** (2.117)	32.068** (5.033)	-58.726** (8.310)	27.568** (3.328)	
<i>Mobile Phone Location Exposure Index (LEX)</i>									
<i>Lagged: 1-day</i>		0.652** (0.111)	0.639** (0.111)	0.647** (0.111)	0.664** (0.115)	0.659** (0.112)	0.637** (0.111)	0.600** (0.111)	0.649** (0.112)
<i>4-day</i>		0.699** (0.112)	0.718** (0.112)	0.713** (0.112)	0.658** (0.116)	0.734** (0.114)	0.711** (0.112)	0.691** (0.112)	0.727** (0.114)
<i>7-day</i>		0.661** (0.113)	0.700** (0.113)	0.686** (0.113)	0.600** (0.116)	0.715** (0.114)	0.683** (0.113)	0.678** (0.113)	0.711** (0.114)
<i>14-day</i>		0.494** (0.113)	0.543** (0.113)	0.510** (0.113)	0.371** (0.117)	0.527** (0.115)	0.511** (0.113)	0.526** (0.113)	0.534** (0.114)
<i>21-day</i>		0.345** (0.112)	0.381** (0.112)	0.357** (0.112)	0.070 (0.116)	0.368** (0.113)	0.354** (0.112)	0.372** (0.112)	0.378** (0.113)
<i>State Policy Stringency Index</i>									
<i>Lagged: 1-day</i>		-1.619** (0.444)	-1.671** (0.444)	-1.640** (0.445)	-1.089* (0.463)	-1.298** (0.453)	-1.643** (0.444)	-1.772** (0.444)	-1.339** (0.452)
<i>4-day</i>		-1.636** (0.444)	-1.531** (0.445)	-1.560** (0.445)	-1.253** (0.463)	-1.063* (0.454)	-1.603** (0.444)	-1.673** (0.444)	-1.095* (0.453)
<i>7-day</i>		-1.755** (0.450)	-1.477** (0.451)	-1.570** (0.451)	-1.537** (0.470)	-1.172* (0.460)	-1.660** (0.450)	-1.653** (0.451)	-1.186** (0.460)
<i>14-day</i>		-2.146** (0.462)	-1.509** (0.464)	-1.954** (0.464)	-2.070** (0.485)	-1.398** (0.474)	-1.955** (0.462)	-1.816** (0.463)	-1.334** (0.474)
<i>21-day</i>		-1.825** (0.476)	-1.054* (0.479)	-1.534** (0.479)	-2.261** (0.505)	-1.289** (0.491)	-1.658** (0.477)	-1.447** (0.478)	-1.132* (0.491)
\bar{R}^2 (21-day lag)		0.024	0.024	0.024	0.028	0.025	0.024	0.024	0.025
<i>Number of Obs.</i>		438,600	438,600	438,600	408,426	431,228	438,600	438,600	431,228

Note: Robust standard errors in parentheses; +p<0.1; *p<0.05; **p<0.01

Table 2: Secondary Panel Regressions – Government & Community Response, Travel intensity & Pairwise Connectedness (May 5-Oct. 23, 2020)

to the mobility of the smartphones between the two states. All else equal, a one percent decrease in travel intensity (as measured by LEX) between the source and the target states leads to a decline of 0.345-0.699 percentage points in the pairwise Covid-19 connectedness (see Column (1)). As we include the CMIs one at a time, the coefficient estimate for the LEX variable does not change much; it fluctuates between 0.354 and 0.734.

The implication of the LEX coefficient is quite straightforward: The higher the travel intensity between two states, the likelier it is to have higher Covid-19 connectedness between the two states. Furthermore, the coefficient estimate for LEX declines as we increase the number of lags from 7 to 14 and 21 days. This is consistent with our expectations. We consider up to 21 lags in our regressions, since Cartenì et al. (2020) points out that 21 days effectively covers the *positivity detection time*, the number of Covid-19 infections that can be transmitted from state i to state j due to travel between two states is likely to drop as the number of lags is increased above 7 days to 14 and 21 days.

This result supports the policy perspective that in the Fall-Winter 2020 wave of the Covid-19 pandemic, implementation of travel restrictions would be effective in curbing the spread of the virus across the U.S. states.

We have already shown in section 3.3 that the states that implemented strict public health measures against the pandemic were able to curb the rate of growth of new cases of Covid-19 (see Table 1). Interestingly, when we incorporate the state-level government stringency index in secondary regressions, the resulting estimates are mostly negative and statistically significant, which implies that strict policy measures do help lower the connectedness of Covid-19 cases across the U.S. states as expected. The coefficient estimate for the GSI (in regressions without the CMIs) increases in absolute value from -1.62 to -2.15 as we increase the number of lags to 4, 17, and 14 days, before declining to -1.83 with 21-day lags. The effectiveness of the state government public health policy measures become more effective as days pass by up to 14 days, but eventually, its effectiveness is likely to experience a downturn.

This result establishes that the stringent state government policy not only reduces the number of cases in the state, but it also reduces the connectedness of new cases from that state to others. On the contrary, lax state government policy not only leads to an increase in the state-level cases but also generates spillovers/connectedness to other states.

Finally, we present the source state to target state ratios of CMIs in the first panel of Table 2. Except for the coefficient estimates of the one-day lagged CMIs and the 4-day lagged *Resdnt*, coefficient estimates for all CMI variables are statistically significant and have the expected sign. Despite the fact that all CMI variables are corrected for potential endogeneity problems, their one-day lagged coefficient estimates are mostly of wrong sign

and statistically insignificant. This result is perhaps a reflection of the fact that it is not meaningful to expect a reaction in Covid-19 cases one day after a decline in CMI variables.

As we increase the number of lags, the coefficient estimates are all of the expected sign. While all other community mobility measures provided by Google track the sharing of non-overlapping segments of social space, the residential space variable is the only one that measures the increased use of private space and hence the lower use of all segments of the social space. The coefficient estimate for the residential space at 7-, 14- and 21-day lags is negative as expected, and it increases in absolute value as the number of lags considered increases from 7 days (-24.8) to 14 days (-63.1). However, as the number of lags is increased further, the dampening effect of the increased residential space use on Covid-19 connectedness declines significantly to -32.1 (in absolute value) at 21-day lag. By itself, this variable shows that the community's response to isolate itself is effective in reducing the connectedness of the virus to other states.

Even though parks provide communities with space that can be used by the members of the community, the use of parks actually did actually have a small but statistically significant contribution to lowering the growth rate of the new Covid-19 cases. As a consequence, we would expect social space use in parks to lower the Covid-19 connectedness across the U.S. states. Consistent with these expectations, the coefficient estimates for the social space use in parks are all negative and statistically significant, varying between -1.2 and -4.8 as the number of lags increases.

As parks offer large open spaces and its use by the members of the local communities is not necessarily in conflict with the social distancing rules. As a consequence, members of the communities that cut the social space use in retail and recreation, grocery and pharmacy, transit stations, and workplaces can continue enjoying the wide parks without running the risk of catching the virus. Hence, the increased use of parks is likely to lower the growth rates of the new Covid-19 cases and hence their connectedness across states.

Among the variables that aim to measure the use of social space, workplace use *WorkP* has higher coefficient estimates in lags 4 through 21 days (varying between 15.4 and 49.8) than the other three measures. Even though the workplace use declined more than the other three measures, it nevertheless appears to contribute to the containment efforts more than the other three measures of community mobility.

According to the coefficient estimates, the decline in the social space use in retail and recreation (*RetRec*) contributed to the decline in connectedness across states more than the social space use in transit stations and groceries and pharmacies. Furthermore, its contribution continues to increase when the number of lags is increased to 14 and 21 days.

The coefficient estimates for the grocery and pharmacy and the transit stations reach

their highest levels at 7-day lags (17.5 and 16.5, respectively) and stabilize around those levels at higher lags of 14 and 21 days considered.

In general, the coefficient estimates of the source-to-target ratios of relative CMIs tend to increase as the number of lags considered is increased from one-day to 7- or 10-day, indicating stronger effectiveness of government or self-imposed restrictions on public space use. As the number of lags is increased further to 14 days, the coefficient estimates decline, which indicates the existence of a peak in the effectiveness of the restrictions on Covid-19 connectedness across states at around 10-days. As expected, the use of parks has very little contribution to Covid-19 connectedness across states because it is possible to comply with social distancing rules in large open areas offered in parks.

Finally, the coefficient estimate for the average of the four CMI variables (*AvgCMI*) turns out to have relatively higher coefficient estimates compared to other CMI variables. This is quite expected because it reflects the behavior of four different measures of social space use, and a decrease in *AvgCMI* would generate a more significant response from the connectedness measures.

To summarize, the coefficient estimates for all CMIs basically show that irrespective of which measure of community variable we use, those states that tend to have high community mobility in public spaces not only end up having a higher case of Covid-19 infections but they are likely to generate connectedness of Covid-19 cases to other states.

So far, in this section, we have shown that proactive government and community response can play a critical role in limiting the connectedness of Covid-19 cases across the U.S. states. In addition, we have shown the critical role played by the between-state traveling in generating connectedness of Covid-19 cases across the U.S. states. Finally, in this section, we will search for econometric evidence about the role politics played in the spread of the virus across states.

Table 3 presents the panel regression of pairwise connectedness on the pairs of state governors' political party affiliation dummies in addition to the variables that were already included in Table 2. In order to save space, in Table 3 we present the results for 7-, 14- and 21-day lagged variables and use only two CMI variables, namely, *Resdnt* and *Avg.CMI*.

As for the dummy variable, $R \rightarrow R$ denotes the dummy variable where the source is a state with a Republican governor while the target is a state with a Democratic governor. Similarly, $R \rightarrow D$ is the dummy variable for the source state with a Republican governor and the target state with a Democratic governor, and $D \rightarrow R$ is the dummy variable for the source state with a Democratic governor and the target state with a Republican governor. The term $D \rightarrow D$ is not included and treated as the reference variable. Statistically significant coefficient estimates for any of the three variables would indicate the difference from the coefficient estimate of the missing dummy variable, $D \rightarrow$

	<i>7-day lag</i>			<i>14-day lag</i>			<i>21-day lag</i>		
LEX	0.466**	0.485**	0.511**	0.291*	0.323**	0.330**	0.139	0.167	0.172
	(0.114)	(0.114)	(0.115)	(0.114)	(0.114)	(0.116)	(0.113)	(0.113)	(0.114)
Stringency	0.007	0.133	0.651	-0.432	-0.037	0.414	-0.019	0.44	0.686
	(0.50)	(0.50)	(0.51)	(0.51)	(0.51)	(0.52)	(0.53)	(0.53)	(0.54)
$R \rightarrow R$	12.35**	12.34**	12.55**	12.47**	12.45**	12.38**	12.57**	12.56**	12.43**
	(0.72)	(0.72)	(0.73)	(0.73)	(0.73)	(0.73)	(0.73)	(0.73)	(0.73)
$R \rightarrow D$	12.73**	12.75**	12.95**	12.69**	12.76**	12.60**	12.86**	12.95**	12.70**
	(0.73)	(0.73)	(0.74)	(0.73)	(0.73)	(0.74)	(0.73)	(0.73)	(0.74)
$D \rightarrow R$	1.315**	1.281**	1.280**	1.470**	1.383**	1.410**	1.404**	1.300**	1.385**
	(0.49)	(0.49)	(0.50)	(0.49)	(0.49)	(0.50)	(0.49)	(0.49)	(0.50)
Residential	–	-25.88**	–	–	-64.6**	–	–	-60.85**	–
		(8.30)			(8.47)			(8.31)	
Avg. CMI4	–	–	25.27**	–	–	30.84**	–	–	27.84**
			(3.47)			(3.48)			(3.33)
No. of Obs.	438,600	438,600	431,228	438,600	438,600	431,228	438,600	438,600	431,228
R²	0.024	0.024	0.026	0.024	0.025	0.026	0.024	0.025	0.026

Note: Robust standard errors in parentheses; +p<0.1; *p<0.05; **p<0.01

Table 3: Secondary (Panel) Regressions – Accounting for Within and Between Group Connectedness of the States with Democratic and Republican Governors (May 5-Oct. 23, 2020)

D.

The coefficient estimate for the LEX variable is positive and statistically significant for the 7- and 14-day lags, but not significant for the 21-day lag. As we have noted in the discussion of Table 2, the effect of travelling on Covid-19 cases and hence their connectedness across states is likely to diminish after 14 days. Therefore, it is no surprise to obtain statistically insignificant coefficient estimates for the 21-day lag.

The second variable in the regression is the government stringency index, whose coefficient estimates become statistically insignificant at all lags. Once we include the dummies for pairs of source and target states on the basis of the governor’s political party affiliation, the stringency of the government policy ends up having no effect on the connectedness across states. This result clearly shows that the governor’s party affiliation directly affectss the stringency of the public health policy against the pandemic.

Third, we focus on the coefficient estimates of the community mobility indicators. Both residential space use and Avg.CMI4 variables are statistically significant and have the expected signs. Their respective coefficient estimates are not much different from what we presented in Table 2.

The coefficient estimates for $R \rightarrow R$ and $R \rightarrow D$ dummies are statistically significant at all lags, and their values vary between 12.3 and 12.95, depending on the lags used

and the inclusion of CMI variables in the regression.¹¹ Both of these estimates are much greater than the coefficient estimate for $D \rightarrow R$, which ranges between 1.28 and 1.47.

The coefficient estimates from the panel regressions of pairwise connectedness measures enforce our findings from the graphical analysis of total directional connectedness measures between the states with Democratic vs Republican governors (see Section 4.2). First, the states with Republican governors tend to generate higher pairwise connectedness to each other and to the ones with Democratic governors compared to the respective measures of connectedness generated by the states with Democratic governors. Second, the within-group connectedness of the states with Democratic governors is statistically higher than the connectedness from the states with Democratic governors to the ones with Republican governors.

6 Conclusion

In this paper, we studied how the regional variation in the implementation of public health policy measures and local community attitudes towards the pandemic, in part shaped by the polarized politics of the presidential elections, determined the local trajectories of Covid-19 cases and their connectedness across the U.S. states.

The public health policy response to the Covid-19 pandemic varied substantially around the world. In the United States case, the federal government failed to put together a public health policy strategy that outlined policy measures against the pandemic at the federal level while guiding and coordinating the states' policies. As a consequence, since the beginning, there has been a wide variation in containment measures implemented by the U.S. states. The state-level public health policy response to the pandemic was excessively politicized, perhaps due to 2020 being a presidential election year.

In addition to documenting the differences in measures such as the government stringency index and the community mobility indicators across the states, we can identify a pattern in these measures across political party lines. State governors' political party affiliations also influenced the trajectories of the Covid-19 cases over time and their connectedness across the states. Unlike the states with Democratic governors, the states with Republican governors, in general, have not implemented strict policy measures against the pandemic. Nor are the communities in these states strictly followed social distancing recommendations of experts.

¹¹ When the panel regressions in Table 3 are repeated with $R \rightarrow R$, instead of $D \rightarrow D$, is designated as the reference variable, the coefficient estimate for $R \rightarrow D$ is not statistically different from zero, indicating that the pairwise connectedness among the states with Republican governors is as high as the pairwise connectedness from states with Republican governors to the ones with Democratic governors.

Our paper is the first in the literature showing that the states with lax government and community response to the pandemic experienced higher new cases of Covid-19 and generated connectedness of Covid-19 cases to each other and to those states that followed stricter policy and community response. Finally, we also found that Covid-19 connectedness across states was quite strongly related to the travel intensity across states, as measured by the mobile phone location exposure index, LEX.

Based on these findings, we conclude that strong government and community responses to the pandemic are needed to bring down the growth rates of Covid-19 infections in each state and lower the connectedness of Covid-19 cases across the states. Finally, we conjecture that once the federal government show leadership in implementing stringent public health policies at the federal level and coordinate the state-level policies, both the Covid-19 cases and their connectedness across the states can be brought under control.

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