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State-Level Health and Economic Impact of COVID-19 in India

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Abstract

The health and economic impacts of COVID-19 on India have been substantial, with wide variation across states and union territories. This paper quantifies the impact of containment measures and voluntary social distancing on both the spread of the virus and the economy at the state level during the first wave of the COVID-19 pandemic. We construct a *de-facto* measure of state-level social distancing, combining containment strigency and observed mobility trends. State-level empirical analysis suggests that social distancing and containment measures effectively reduced case numbers, but came with high economic costs. State characteristics, such as health care infrastructure and the share of services in the economy, played an important role in shaping the health and economic outcomes, highlighting the importance of adequate social spending, health care infrastructure, and social safety nets.

JEL Classification Numbers: C33, E65, O53, R11

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Contents

I. INTRODUCTION

The health and economic impacts of COVID-19 on India have been substantial. As of June 24, 2021, India has more than 30 million confirmed cases, the second highest number in the world. The stringent national lockdowns led to a 24 percent decline in GDP in the second quarter of last year, the largest among G20 countries. Behind the headline numbers, the health and economic outcomes of the pandemic vary considerably by state, as highlighted by daily case numbers, energy consumption, nitrogen dioxide (NO_2) emissions, and mobility.

In this paper, we develop a *de-facto* state-level social distancing measure by combining an ordinal index of containment stringency and observed mobility trends at the state level. We use this measure to quantify the impact of containment measures and voluntary social distancing on health and economic outcomes at the state level. We also examine the role of state-level factors, such as health infrastructure, population and economic characteristics, and governance, in shaping these outcomes.

Our paper is related to the rapidly expanding literature on the effectiveness of containment measures, which consists of two broad strands: modelling approaches and empirical estimates. Many of the model analyses, such as Eichenbaum, Rebelo and Trabandt (2020), Engler et al. (2021), Forslid and Herzing (2020), and Brotherhood et al. (2020) use the susceptible, infectious, and recovered (or SIR) epidemiological model to understand the impact of containment measures. Kahalé (2020) examines the economic impact of social distancing measures using the susceptible, infectious, and susceptible (or SIS) compartmental model which assumes that the infection does not confer lasting immunity. The empirical literature has examined COVID-19 containment internationally in cross-country studies (Deb et al. 2020a, b; Hsiang et al. 2020; and IMF 2020a, b) and China-specific studies at the beginning of the pandemic (Kraemer et al., 2020, Chinazzi et al. 2020, and Tian et al., 2020).[2] More recently, empirical analyses examine the impact of containment measures on economic activities in India by considering nighttime lights and electricity consumption (Beyer, Franco-Bedoya, and Galdo 2021, Beyer, Jain, and Sinha 2020). In our paper, we not only analyze the economic impact of COVID-19 in India, but also consider the health effects and the role of state-level factors in determining the effectiveness and success of containment measures.

[2] For a more detailed literature review on cross-country studies, see Deb et al. 2020a, b.

Our empirical approach follows Deb et al. (2020a, b) and IMF (2020a) and applies local projections methods (Jordà 2005) to study the impact of effective state-level social distancing on health and economic outcomes. We construct a comprehensive state-level dataset for India at daily frequency, covering high frequency health and economic-related indicators and state-level characteristics such as health and economic structures, population characteristics, income, and governance. The sample period runs from mid- February 2020 to mid- January 2021, which covers the the course of the first wave of the pandemic in India. The lessons drawn from the first wave are important in informing discussions on how best to target social distancing and containment measures as well as economic policies to local factors in the subsequent waves and potential future health crises.

Our results suggest that social distancing and containment measures have been effective in reducing the number of COVID-19 cases but have come with economic costs. These measures were most effective in reducing COVID-19 cases where the health infrastructure was strong, the share of vulnerable population[3] and literacy rates were high, and where population density was low. Social distancing and containment measures had the most adverse economic impact in states where the share of services and urbanization was high, and the effects tended to be more persistent in states with lower GDP per capita and weaker health care infrastructure. In addition, governance played an important role in both health and economic outcomes. Social distancing and containment measures had the most health benefits and the least economic cost in states with better governance.

The rest of the paper is structured as follows. Section II discusses the data and stylized facts on state-level variations of the COVID-19 pandemic. Section III discusses the links between mobility and containment and presents the effective social distancing measures at the state-level. Section IV presents the empirical methodology. Section V discusses baseline results of the impact of effective social distancing. Sections VI and VII present results on the role of state-level factors on health and economic outcomes, respectively. Finally, Section VIII offers concluding remarks and policy recommendations.

II. Data and Stylized Facts

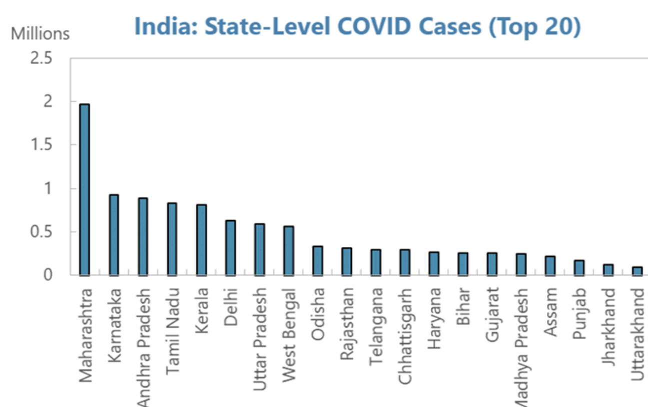
For our empirical analysis, we construct a comprehensive state-level dataset for India at daily frequency. For mobility, we consider Google mobility at the state level and consider two containment measures: one developed by the IMF and another by Oxford University. For

[3] In this paper, vulnerable population refers to population with co-morbidities and population aged 60 and over.

health-related indicators, we focus on the official confirmed cases at the state level from CEIC. For daily economic indicators at the state level, we consider electricity consumption data from Power System Operation Corporation Limited (POSOCO), NO_2 emissions data from the Air Quality Open Data Platform, and flights data from FlightRadar24. On state-level characteristics, we examine health care infrastructure such as health care spending per capita and doctor density; population density; demographics, such as the share of the population aged 60 and over and with comorbidities; and economic structure, such as the share of services, GDP per capita, and governance. [4] The data on state-level characteristics are compiled from multiple sources, including the Reserve Bank of India, National Statistical Office, National Institute of Public Finance and Policy, Census of India, Density of India State of Population Census, Centre for Monitoring Indian Economy (CMIE), and CEIC. The detailed definition of the data series and their sources can be found in Annex Table A1. The sample period for daily data is from mid-February 2020 to mid-January 2021, which covers the first wave of the pandemic in India. The data on state-level characteristics is based on the latest available information.

The COVID-19 pandemic has had differentiated health and economic impacts across states and union territories. For both the absolute number of confirmed cases and confirmed cases per capita, Maharashtra, Kerala, Karnataka and Andhra Pradesh were among the worst hit states during the first phase of the pandemic (Figure 1).

Figure 1: State-level Heterogeneity: Health Outcome

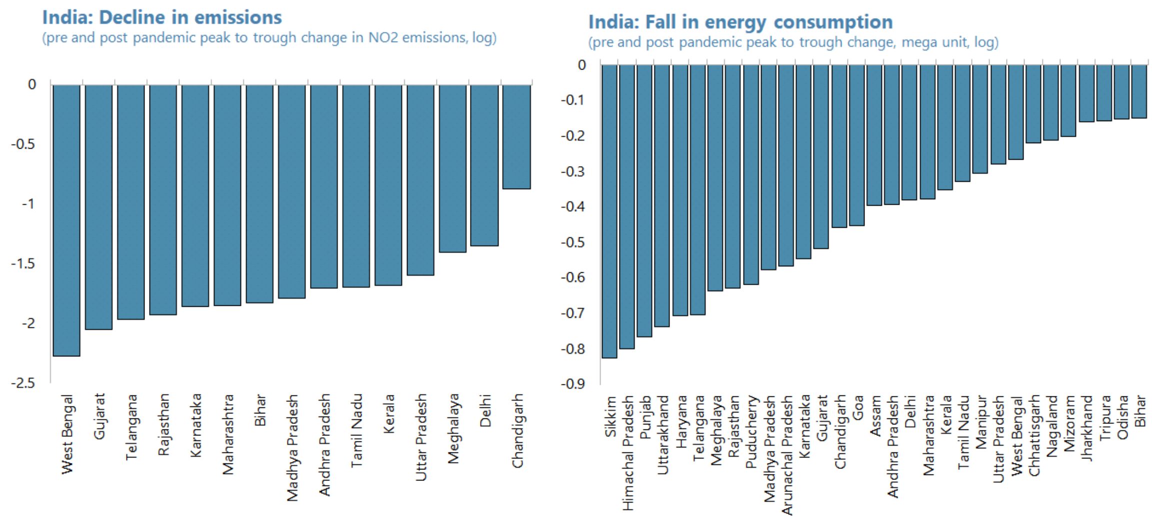


Source: CEIC. Last date: January 12, 2021.

[4] Some of characteristics are also found to be important in determining the effectiveness of social distancing and containment measures in cross country studies, such as Deb et. al. (2020a and b).

Economic outcomes among states were also significantly heterogeneous, as evidenced by the peak-to-trough change in NO_2 emissions and energy consumption.[5] For example, NO_2 emissions declined the most in West Bengal and Gujarat, while falls in energy consumption were largest in states such as Sikkim, Himachal Pradesh, and Punjab (Figure 2).

Figure 2: State-level Heterogeneity: Economic Outcome



Sources: Air Quality Open Data Platform of the World Air Quality Index

Sources: Power System Operation Corporation Limited (POSOCO)

In addition, the decline in mobility varied across states, reflecting the timing and severity of the pandemic in states and efforts to combat it. While the general trend is similar, particularly in the early phase that coincided with the national lockdown that started on March 25th, 2020, movements of Google mobility across states and across time in the later period differ considerably, where containment efforts were more decentralized, relying on local containment zones. For example, in mid-April 2020, the government announced several relaxation measures in geographical areas designated as non-hotspot (orange and green zones). At the end of July 2020, the central government issued guidelines to further paving the way for a phased re-opening of activities across the country and limiting the lockdown only to containment zones.[6] As seen in Figure 3, the decline in mobility in Maharashtra, among the worst-hit states, is much more marked than in Rajasthan.

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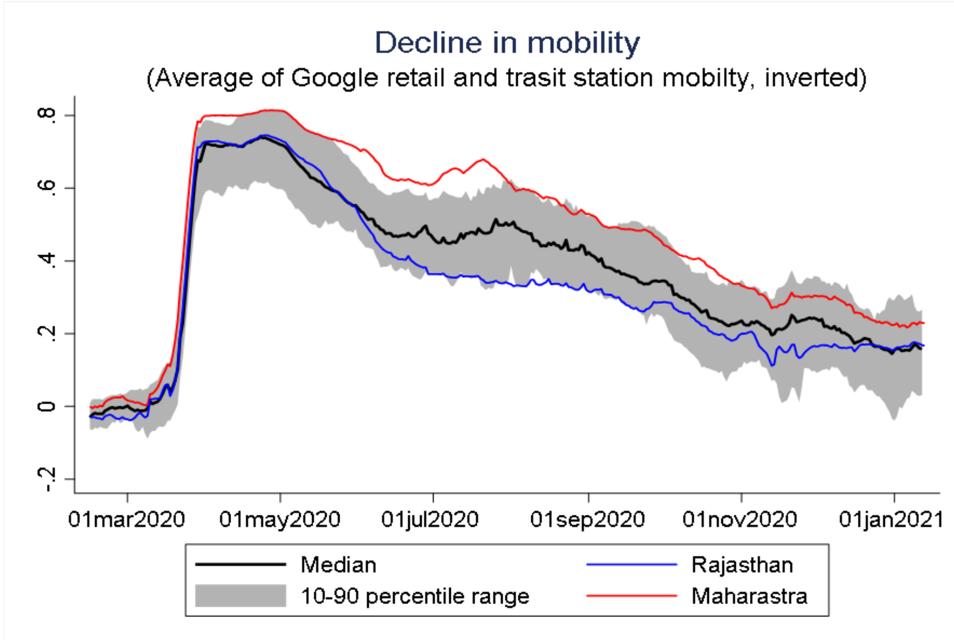
[5] As noted in Deb et al. (2020b), NO_2 emissions are strongly correlated to lower-frequency (monthly) economic variables such as industrial production at an international level. Over the longer term, there exists a robust relationship between conventional measures of economic activity such as annual GDP growth, growth in manufacturing value added and growth in measures of industrial production and NO_2 emissions. The energy consumption data from POSOCO captures both industrial and household consumption.

[6] For details on containment measures, see announcements by the Ministry of Home Affairs, Government of India at https://www.mha.gov.in/

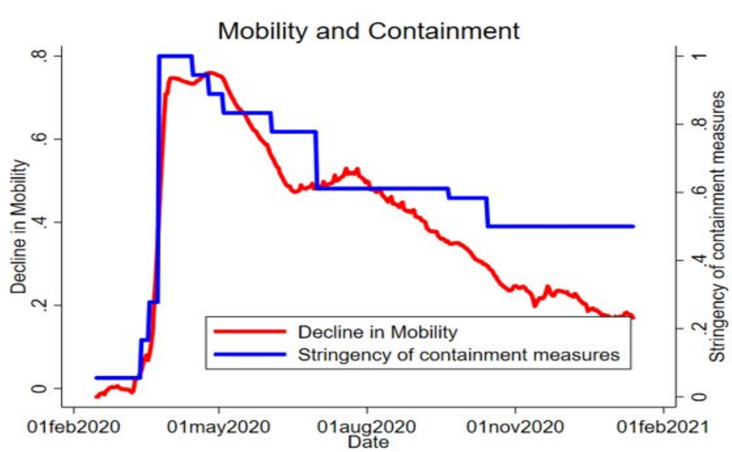
Figure 3: State-level Heterogeneity: Observed Mobility



Sources: Google Mobility and IMF Staff Calculations.

III. Mobility, social distancing, and containment

Figure 4: National-Level Mobility and Containment



We construct a measure of state-level social distancing and containment by using both a national-level stringency index and data on state-level mobility.[7] This approach allows us to assess the interaction between the national-level stringency index and state-level mobility to capture the impact of "official" containment measures and "voluntary" social distancing (IMF 2020c). On national-level stringency, we use a new IMF containment index (see Furceri, Kothari and Zhang, 2021), which covers six economic sectors (international travel, schools, retail, industry, services, and public gatherings). Compared with other indices (such as Hale and others 2021), the new index has two advantages: it distinguishes between key economic sectors (services, industry, retail)—thus providing a granular view of containment measures—and it captures announcements about future changes to containment measures.[8]

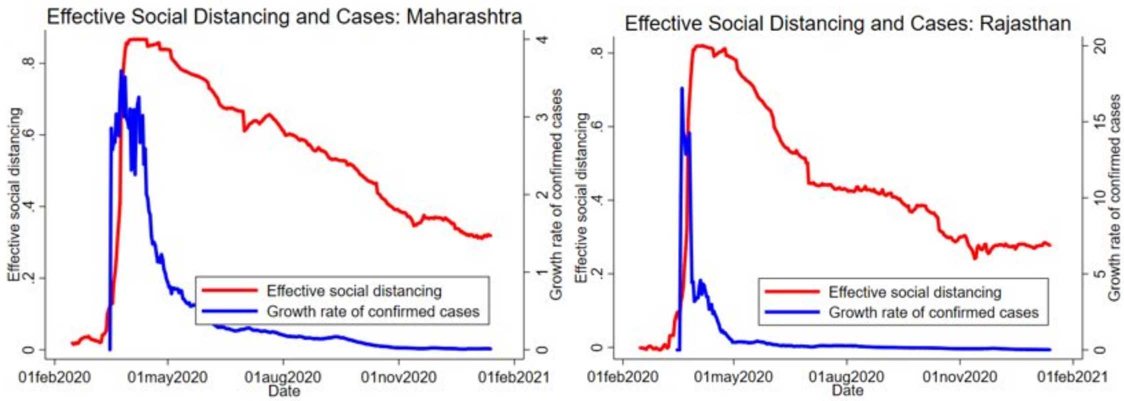
We focus on two components of Google mobility indices (retail and recreation mobility and transit stations mobility) that have the highest absolute correlation with the Oxford Stringency Index in India. Retail and recreation can be interpreted as a proxy for discretionary spending and can be used to study how COVID-19 has impacted consumer behavior. Transit station mobility, on the other hand, can be regarded as a proxy for changes in workplace behavior.

The state-level effective social distancing indices highlight differences across states. While the initial spike in social distancing was largely driven by stringent national lockdowns, we observe state-level divergence in social distancing and containment as states reopened. Figure 5 presents the evolution of the effective distancing index and the daily growth rate of COVID-19 cases for two states: Maharashtra and Rajasthan. A common feature across the two states is that a high degree of effective social distancing coincides with a sharp reduction in the growth rate of confirmed cases.

[7] We consider the average of national-level stringency index and state-level mobility data. As a robustness check, we also examine alternative definitions of social distancing, including 1) state-level mobility only; and 2) principal component analysis of national-level stringency and state-level mobility data. The results are found to be robust (see Section IV.B and Figure A1).

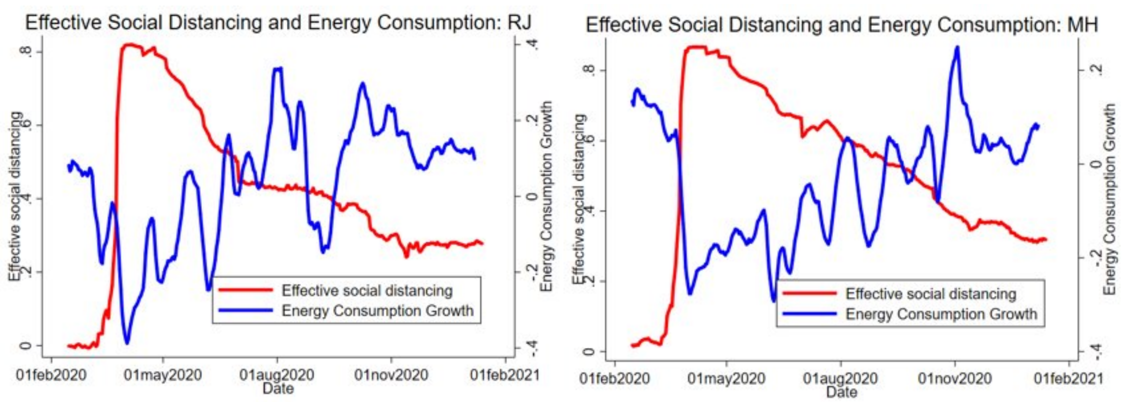
[8] We also considered robustness checks using the Oxford stringency index and the results are found to be robust, see Section IV.B and Figure A1.

Figure 5: State-Level Effective Social Distancing and Cases



Similarly, we observe a common negative relationship between the degree of social distancing and containment and energy consumption at the state-level, even though states tend to have different energy consumption patterns (Figure 6).

Figure 6: State-Level Effective Social Distancing and Energy Consumption



IV. The Impact of Effective Social Distancing

We follow the methodology of Deb et al. (2020a, b) and IMF (2020a), applied at the regional level in India, to study the impact of effective state-level social distancing on health and economic outcomes. Establishing causality is difficult in this context because the decision to implement containment measures crucially depends on the evolution of the virus, which, in turn, may affect mobility and economic activity (Maloney and Taskin 2020). We address this by controlling for the lagged values of COVID-19 infections and economic variables in our specification. Given we have data at the daily frequency, this allows us to effectively control for the endogenous response of containment measures and social distancing to the spread of COVID-19. To further account for the expected evolution of the pandemic in each state and other unobservable variables, we include state-specific time trends and fixed effects. The fixed effects also capture all time-invariant state-level differences.

Our basic framework is based on Jordà's (2005) local projections methods, where we look at the impulse response of containment measures on health outcomes captured by the number of COVID-19 cases and various economic variables. In essence, we use a "difference-in-difference" approach that allows us to compare the dynamic evolution of infected cases and economic variables before and after the day of the introduction of social distancing (treatment) in a given state (treatment group) with that of another state (control group) that has not instructed the social distancing on the same day. The regression we estimate is:

$$\Delta I_{i,t+h} = u_i + \mathrm{q}_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta I_{i,t-\ell} + \varepsilon_{i,t+h} \quad (1)$$

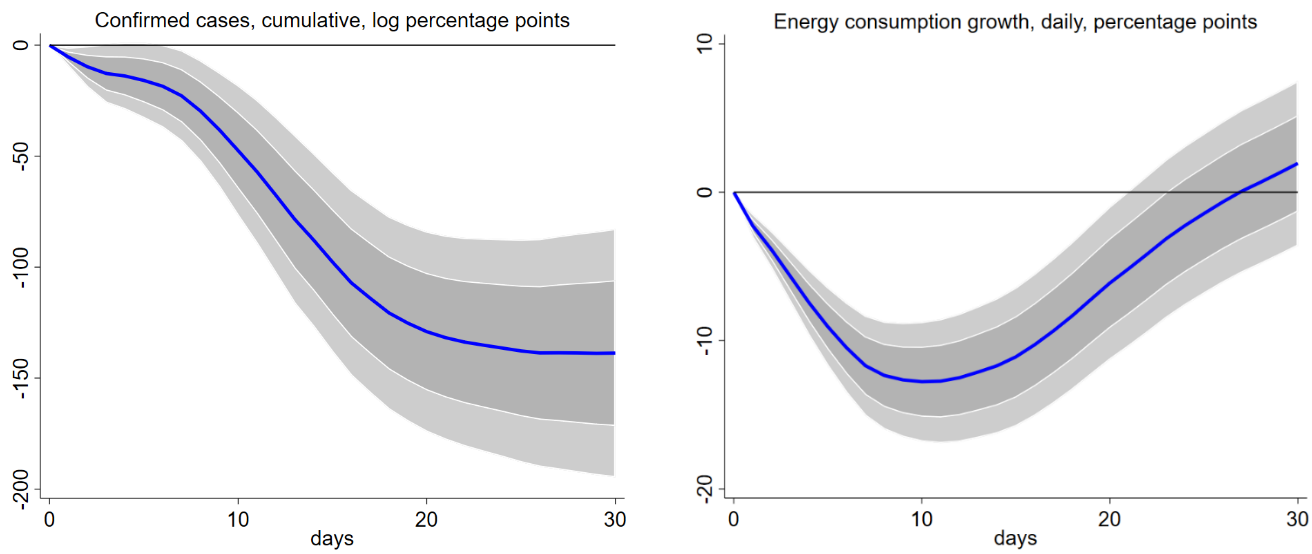
$\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections or economic indicator in state i at date t, $c_{i,t}$ denotes the measure of effective state-level social distancing described in Section III; X is a vector of control variables, including lags and state-specific time trends; and u_i captures state-level fixed effects, including potential state-level differences in data quality.

Equation (1) is estimated for each day *h*=0,..,30. Impulse response functions are computed using the estimated coefficients θ_h, and the 95 and 75 percent confidence bands associated with the estimated impulse-response functions are obtained using the estimated standard errors of the coefficients θ_h, based on robust standard errors clustered at the state level. Our sample consists of a balanced sample of 34 states. The estimation period is February 15, 2020 to January 12, 2021, which covers the first wave of the COVID-19 pandemic in India.

B. Aggregate Results

Figure 7 shows the estimated dynamic cumulative response of the number of confirmed COVID-19 cases and the growth in energy consumption to a unitary change in the effective social distancing and containment index over the 30-day period, together with the 95 and 75 percent confidence intervals around the point estimates. We find that while social distancing and containment has been very effective in reducing the number of COVID-19 cases, with cases declining by around 80 percent[9] relative to a baseline of no social distancing and containment, it has come at a large economic cost, with energy consumption growth on average declining by around 12 percentage points after about 10 days, but recovering somewhat thereafter.[10]

Figure 7: Impact of Effective Social Distancing



Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + q_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections or economic indicator in state i at date t. The model is estimated at each horizon $h = 0, 1, \ldots H$, with a lag structure $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

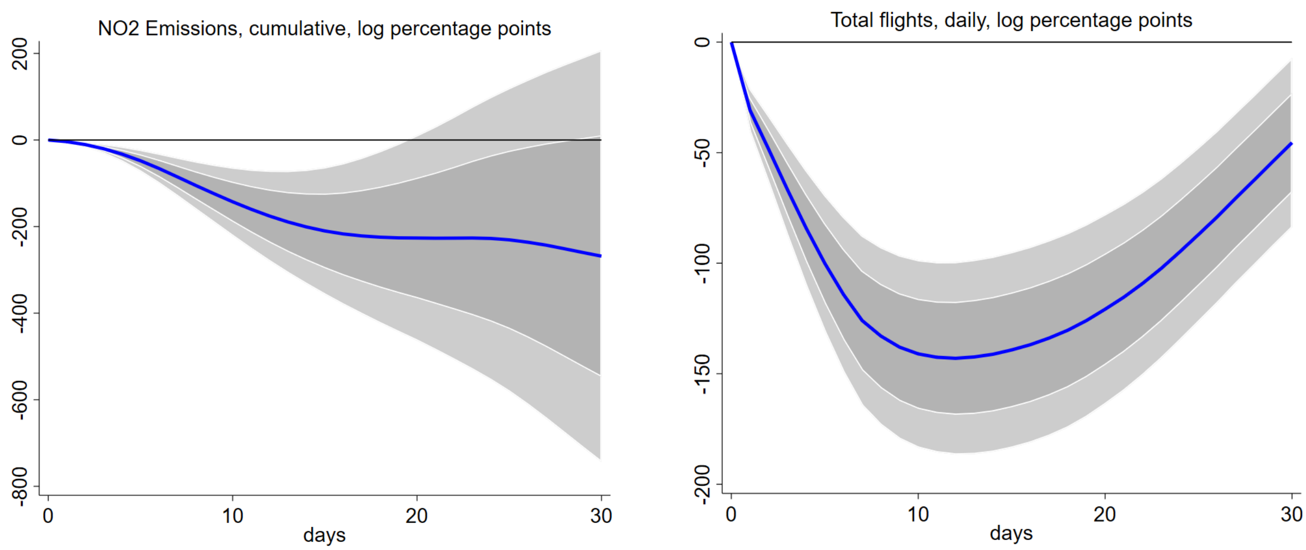
Results are similar to alternative high frequency proxies for economic activity. Figure 8 shows the results for two such measures: the level of NO_2 emissions and the number of flights. NO_2 emissions are strongly associated with the level of economic activity, particularly manufacturing. Using cross-country data during the COVID-19 pandemic, Deb et al. (2020b) confirms a statistically significant relationship between NO_2 emissions and industrial production indices using a monthly database of industrial production indices for 38 countries and monthly levels of NO_2 emissions. The results suggest that our measure of effective social distancing significantly reduced the amount of NO_2 emissions. In states

[9] For confirmed cases, the figures show the impulse responses in log-percentage points. We use the formula, $(e^{q_h} - 1) * 100$, to convert the results in logarithms to percent.

[10] Detailed regression results underlying the impulse responses in Figures 7 and 8 can be found in Annex Tables A3 and A4.

where stringent social distancing and containment were implemented, these may have reduced the amount of NO_2 emissions cumulatively by almost 86 percent after 30 days, relative to a baseline of no social distancing and containment. Looking at a more sector-specific indicator in the form of number of flights, the results show a decline of over 75 percent at its peak.

Figure 8: Impact of Effective Social Distancing on other proxies for economic activity



Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + q_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections or economic indicator in state i at date t. The model is estimated at each horizon $h = 0, 1, \ldots H$, with a lag structure $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

Our results are found to be robust to alternate specifications. While our baseline measure of effective social distancing combines the *de-jure* measure of containment measures at the national and state level with *de-facto* social distancing measured by Google mobility (which incorporates the de-jure element with voluntary social distancing), our results remain largely unchanged if we only focus on the *de-facto* measure (Google mobility). In addition, our results continue to hold if we combine information contained in the index of official containment measures with mobility trends using principal component analysis (Figure A1). Furthermore, the results are robust to alternate econometric specifications, such as different lag structures, longer projection horizons and alternative standard errors (e.g., Driscoll-Kray). The results are also robust to different sub-samples and additional controls, including non-linear trends and daily time fixed effects.

V. What Drives Heterogenity at the State Level?

A. Methodology

Multiple factors could drive the effectiveness of social distancing and containment measures on health and economic outcomes, many of which are interrelated. In this paper, we consider six broad categories of factors: (i) health infrastructure, (ii) vulnerability of the population to COVID-19, (iii) ease of social distancing, (iv) economic structure, (v) income level, and (vi) government effectiveness. Within each category, we identify different proxies which *a priori* capture different dimensions. These factors vary widely across states but are also inter-related. For example, richer states (captured by higher state level GDP per capita) tend to have better health infrastructure and are more urbanized. Annex Table A2 shows the correlation matrix for the factors that capture state characteristics.

We employ an augmented specification of equation (1) to address the issue of whether the estimated effects vary across states depending on state-specific characteristics. To allow the impulse responses to vary with state-level characteristics, we augment our local projections using the smooth transition autoregressive model developed by Granger and Terävistra (1993).

$$\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h} \quad (2)$$

with $F(z_{it}) = exp^{-\gamma z_{it}}/(1 - exp^{-\gamma z_{it}}), \quad \gamma > 0$

where *z* is a state-specific characteristic normalized to have zero mean and a unit variance.

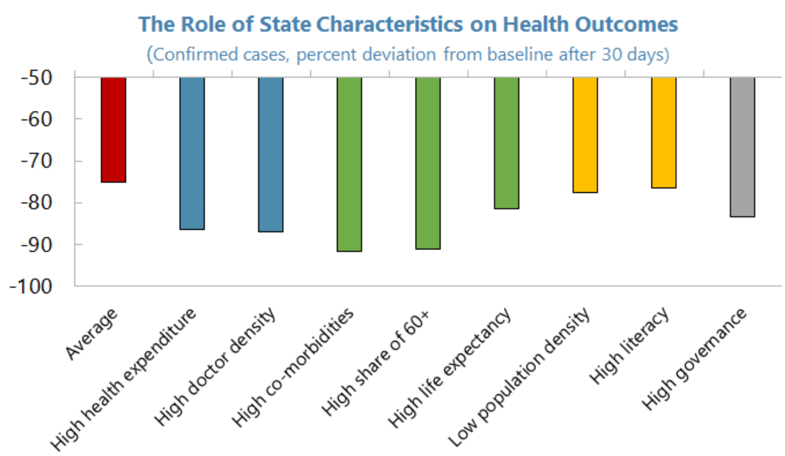
The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(.)$, so that $F(z_{it})$ can be interpreted as the probability of being in a given regime. The coefficients θ_h^L and θ_h^H capture the impact of social distancing at each horizon *h* in cases of very low levels of z ($F(z_{it}) \approx 1$ when *z* goes to minus infinity) and very high levels of z ($1 - F(z_{it}) \approx 1$ when z goes to plus infinity), respectively. $F(z_{it})$=0.5 is the cutoff between low and high country-specific policy responses—for example, low or high health infrastructure.

The advantage of this approach is two-fold. First, compared with a model in which each dependent variable would be interacted with a measure of country-specific characteristics, it permits a direct test of whether the effect of containment measures varies across different state-specific "regimes". Second, compared with estimating structural vector autoregressions for each regime, it allows the effect of containment measures to vary smoothly across regimes by considering a continuum of states to compute impulse responses, thus making the functions more stable and precise.

B. Results: Heterogenity in Health Outcomes

The empirical results confirm our hypotheses that social distancing and containment measures tend to be more effective in reducing the number of COVID-19 cases in states with stronger health infrastructure; higher shares of vulnerable populations (co-morbidities and population aged 60 and over) and literacy rates; lower population density; and better governance (Figure 9). Below we discuss these results in more detail.

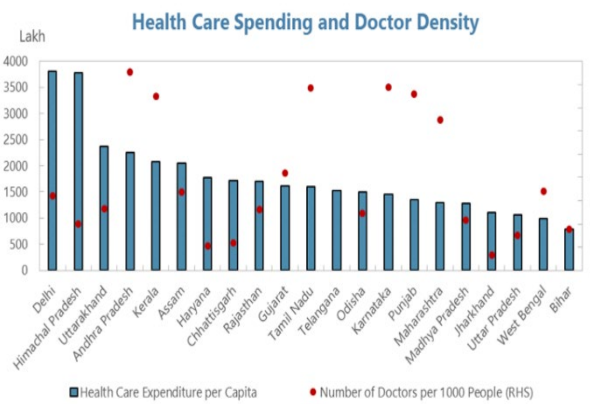
Figure 9: Summary Results: The Role of State Characteristics on Health Outcomes



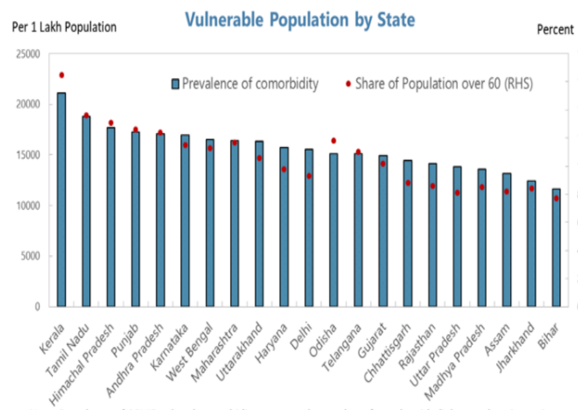
Note: The results captures the role of state level factors in determining the effectiveness of social distancing and containment measures on confirmed cases. The bars measures the percent deviation compared with a baseline without social distancing and containment measures. Impulse responses are estimated based on the local projection approach using daily panel data across Indian states and union territories from February 15, 2020 to January 12, 2021.

The first set of factors focuses on health infrastructure. The hypothesis is that better health infrastructure can make social distancing more effective by allowing for greater testing, contact tracing, and containment. We proxy the health infrastructure of a state by looking at the heath care spending per capita and doctor density. The states vary widely, and, while the two proxies are correlated, they provide distinctly different rankings. For example, Delhi, Himachal Pradesh, and Uttarakhand have among the highest health care expenditures per capita, while Andhra Pradesh, Tamil Nadu, and Karnataka have relatively high doctor density measured by the number of doctors per 1,000 people (Figure 10). The impulse responses in Annex Figure A2 suggest that the states' health infrastructure plays an important role, with social distancing measures resulting in a much larger and statistically significant reduction in the number of COVID-19 infections in states with higher *per-capita* health expenditure and higher doctor density[11]. For example, the number of confirmed cases would decline by close to 90 percent for states with high health expenditure and doctor density, relative to a baseline of no social distancing and containment (Figure 9).

Figure 10: State-level Heterogeneity: Health Infrastructure and Vulnerable Population



Sources: RBI (2020), CMIE, CEIC, and IMF staff calculations.
Note: One Lakh = One Hundred Thousand. Health care expenditure refers to 2019-20 data. Doctor density refers to 2016 data (latest available).



Note: Prevalence of COVID related comorbidity captures the number of people with diabetes, chronic respiratory diseases, cardio vascular diseases and cancer per 1 lakh population (2017). One Lakh = One Hundred Thousand. The share of population over 60 refers to projections for 2021.
Sources: RBI, and IMF staff calculations.

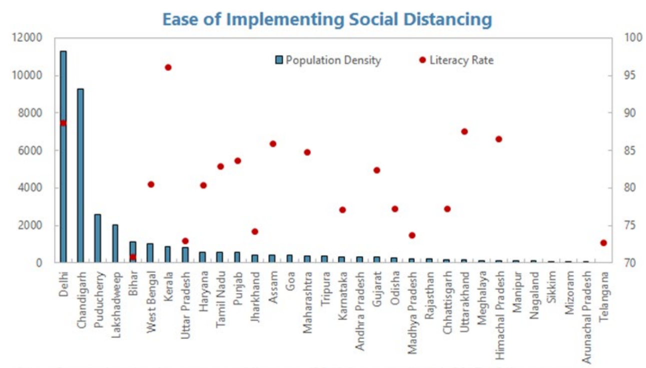
Next, we focus on the share of vulnerable population by state. The vulnerable population is proxied by the share of the population with comorbidities (with diseases such as diabetes mellitus, chronic respiratory diseases, cardiovascular diseases, or cancer), the share of over-60 population, and life expectancy. States such as Kerala and Tamil Nadu have a relatively high share of population with comorbidities and over-60s (Figure 10). The impulse responses show that states with a larger share of population with comorbidities tend to benefit more from social distancing (Annex Figure A3). It is likely that states with higher comorbidities witness a greater impact from social distancing and containment measures because of better adherence to the measures and reduced movements of those who may be asymptomatic. Similar results are obtained when we focus on alternative measures of vulnerable population such as the share of people above the age of 60 or life expectancy (Annex Figure A4).

The third set of variables of interest is related to the ease of social distancing. In general, social distancing is likely to be more effective in less densely populated areas and in areas with lower urbanization. Adherence to social distancing and containment measures are likely to be better in areas with higher literacy, both as a result of better understanding of the

[11] Detailed regression results underlying the impulse responses can be found in Annex Tables A5 and A6. The remaining regression tables are available upon request.

measures and the need and reasons behind it, as well as greater ability to social distance, for example, through remote working. As can be seen in Figure 11, state-level heterogeneity is sizeable in population density and literacy rate. Impulse responses, shown in Annex Figure A5, confirm both hypotheses. We find that low population density is associated with a significant reduction in case counts, while the results for high population density states are less robust, as containment is likely to be more effective when population density is low. Similarly, while the impact of containment and social distancing measures are not significant in states with low literacy, states with higher literacy see greater-than-average benefits from social distancing, with a larger reduction in the number of COVID-19 infections.

Figure 11: State-level Heterogeneity: Ease of Implementing Social Distancing



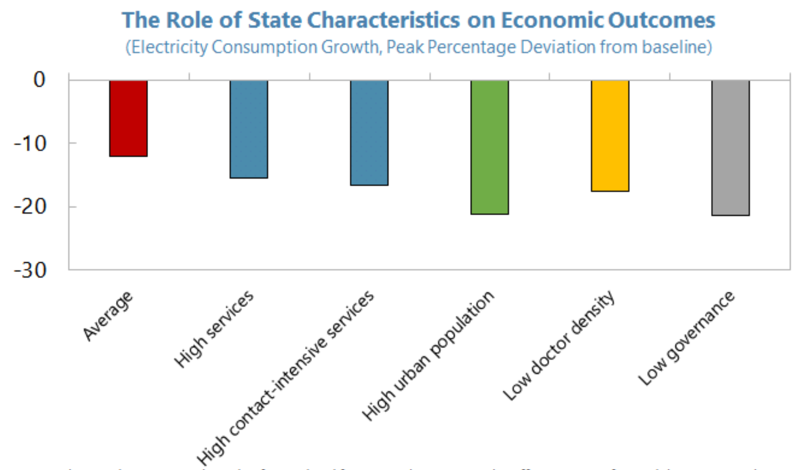
Note: Population density per square kilometer (2011, latest available). 2017-18 literacy rate.
Sources: National Statistical Office (2018) and Census of India (2011).

Furthermore, we examine the role of government effectiveness on health outcomes. Social distancing and containment measures are likely more effective in states with high government effectiveness, due to better implementation of containment measures, contact tracing, and deployment of health care supply. In our analysis, government effectiveness is measured by a governance performance index published by the National Institute of Public Finance and Policy (Mundle et al. 2012). The index captures six components, including infrastructure services delivery, social services delivery, fiscal performance, law and order, judicial services delivery, and the quality of legislature. The results based on impulse responses indeed suggest that high government effectiveness is associated with a significant reduction in case counts (Annex Figure A9).

C. Results: Heterogenity in Economic Outcomes

On the economic front, we find that social distancing and containment measures have the most adverse impact in states with higher shares of services (particularly contact-intensive services) and urbanization. In addition, the impact tends to be more persistent in states with lower income, weaker health care infrastructure (lower doctor density), and lower government effectiveness (Figure 12).

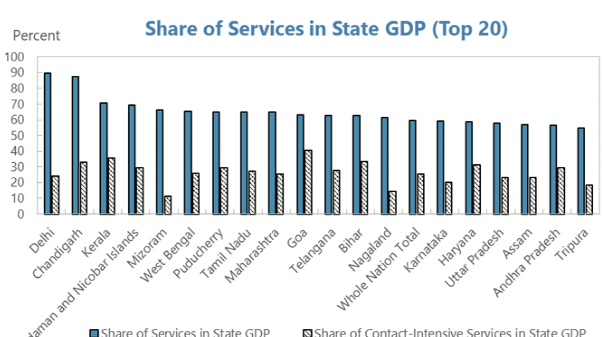
Figure 12: Summary Results: The Role of State Characteristics on Health Outcomes



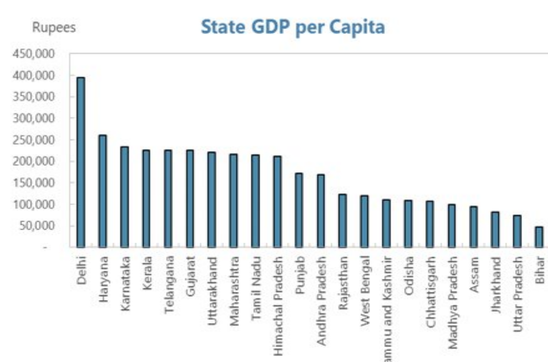
Note: The results captures the role of state level factors in determining the effectiveness of social distancing and containment measures on electricity consumption growth. The bars measures the peak percentage deviation compared with a baseline without social distancing and containment measures. Impulse responses are estimated based on the local projection approach using daily panel data across Indian states and union territories from February 15, 2020 to January 12, 2021.

It is not surprising that the impact of social distancing and containment measures on economic activities depends on the economic structure at the state level. Social distancing is likely to impact services more, particularly contact-intensive services. As can be seen in Figure 13, the share of services varies considerably by state, with Delhi and Chandigarh the states with the highest share of services in state GDP. Furthermore, urban centers are likely to be more affected because of a greater disruption to economic activities from COVID-19 and more intensive enforcement of containment and social distancing.

Figure 13: State-level Heterogeneity: Economic Structure and Income



Source: CMIE. Latest available as of 2014/2015 data.
Note: Contact-intensive services refer to trade, hotels, transportations, storages and communications.



Source: RBI (2020). State GDP per capita for 2018-2019.

The empirical results confirm that states with a higher share of services and contact-intensive services witness a larger decline in energy consumption growth (Figure A6). A similar result holds for the share of urban population, where we see a sharp decline in energy consumption immediately following social distancing, with a gradual recovery over time as people adapt to more flexible ways of work, such as remote working in urban areas (Figure A7).

On income levels and health infrastructure, we hypothesize that richer states may be affected economically initially, but the impact may be less persistent (Figure 13). Part of the reason is that richer states can provide greater support and adapt faster, for example, with more people employed in factories or high-skill service jobs that can adjust more readily to new operating environment and potentially telework. Our empirical results confirm that richer states are better able to adapt to social distancing, even if they are more affected initially. Annex Figure A8 shows that richer states are more affected by social distancing after about a week to a fortnight compared with poor states, but they also tend to bounce back after about 20 days, while poorer states see a more persistent decline.

On better health infrastructure, we show earlier that containment and social distancing is more effective, leading to a greater decline in COVID-19 cases (Annex Figure A2). A similar result is borne economically, where we find that the economic costs in states with higher doctor density are smaller and more transitory, with faster pandemic control resulting in positive benefits after about 20 days (Annex Figure A9). In other words, better health infrastructure can help a state bounce back from the pandemic faster, containing the overall economic fallout. In contrast, states with poorer health infrastructure witness a more prolonged outbreak and a larger and more persistent economic impact.

Finally, on government effectiveness, we found that low government effectiveness is associated with a more profound and persistent impact on economic activities, while the impact is lower and more transient in states with high government effectiveness. Part of the reason is that better governance is associated with better enforcement of containment and social distancing together with better infrastructure and delivery of services, therefore limiting the overall economic losses.

VI. Conclusions and Policy Discussions

The health and economic impacts of COVID-19 on India have been substantial, with states varying considerably in both health and economic outcomes. In this paper, we quantify the impact of containment measures and social distancing on both the health and economic fronts at the state level in India. In doing so, we develop a *de-facto* state-level social distancing measure by combining an ordinal index of containment stringency and observed mobility trends at the state level. We also examine the role of state-level factors, such as health infrastructure, population, and economic characteristics, including the share of services in the economy and governance.

The empirical analysis suggests that social distancing and containment measures were very effective in reducing the number of COVID-19 cases but came at a high economic cost. Social distancing was most effective in reducing cases in states with strong health infrastructure; high shares of vulnerable populations (co-morbidities and population over 60) and literacy rates; and low population density. The most adverse economic impact was observed in states where the shares of services (particularly contact-intensive services) and urbanization were high. In addition, economic impact was more persistent in states with lower GDP per capita and weaker health care infrastructure. It also turns out that governance plays an important role in both the health and economic outcomes, with social distancing having the most health benefits and the least economic costs in states with better governance.

The results highlight that adequate spending and better health care infrastructure are crucial in containing health crises. Better health care infrastructure leads to more effective containment and social distancing, limiting health and economic costs. Strong governance is important in the effective implementation of social distancing and containment measures and in limiting its economic fallout. Given the large economic impact on services and urban centers, the results highlight the importance of ensuring that the social safety net adequately supports the most vulnerable populations, including the urban poor and in service-intensive sectors.

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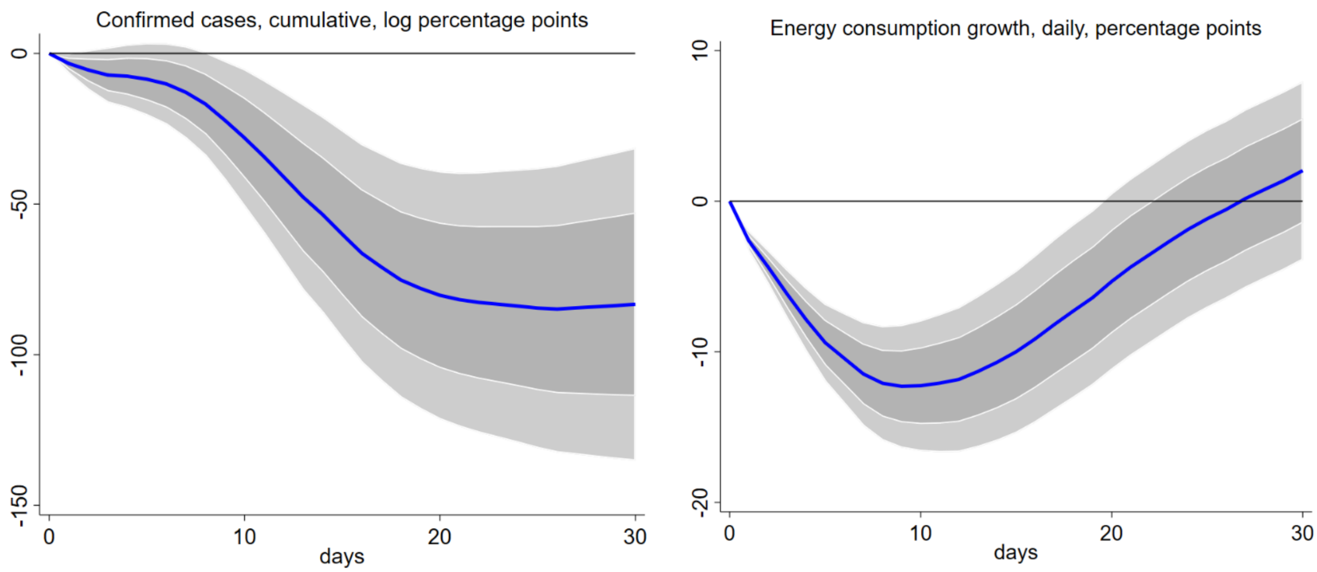
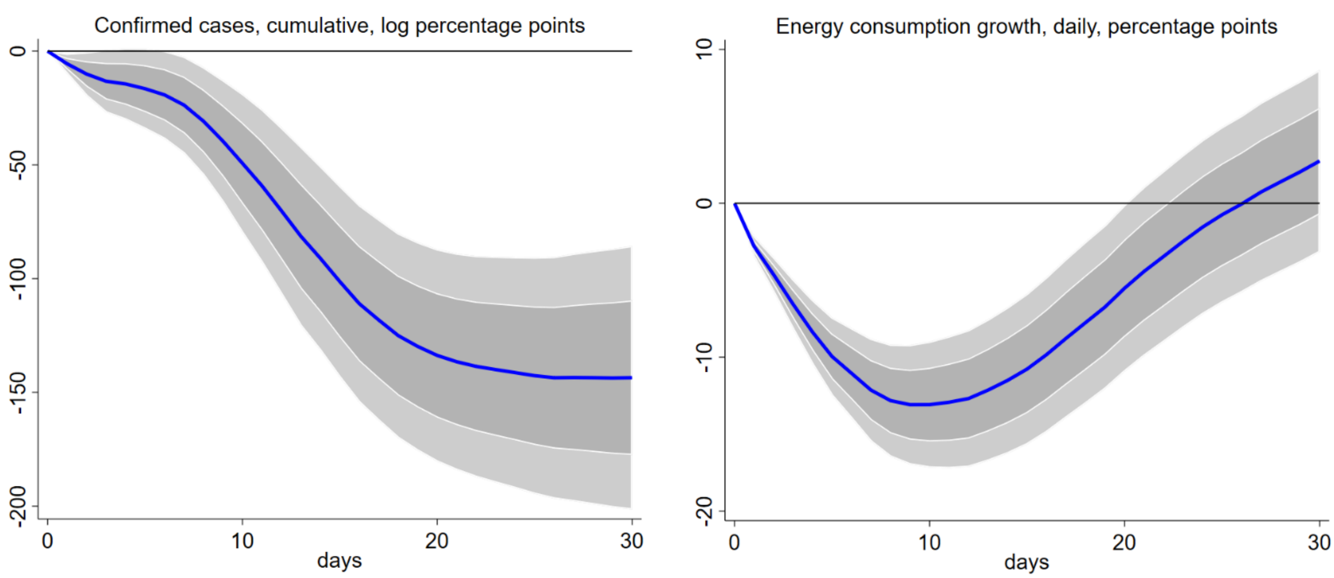
ANNEX FIGURES

Figure A1: Robustness to alternative measures of social distancing

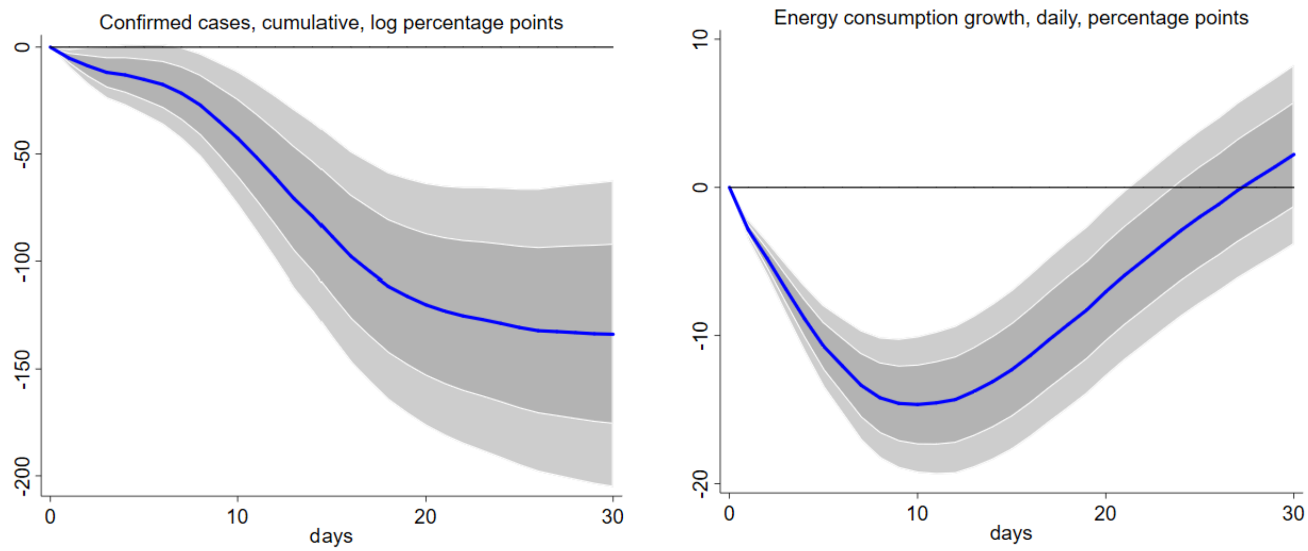
Social distancing measured by state level changes in mobility only



Social distancing measured by Principal Component Analysis (PCA) of official containment measures and mobility



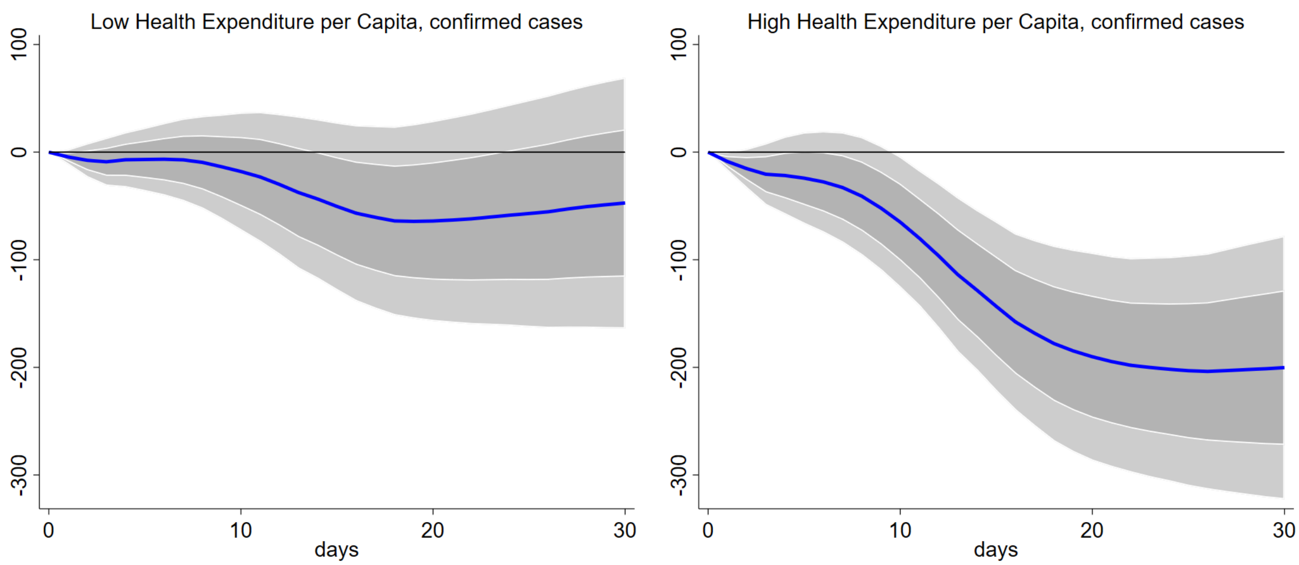
Social distancing measured by the Oxford stringency measure and mobility



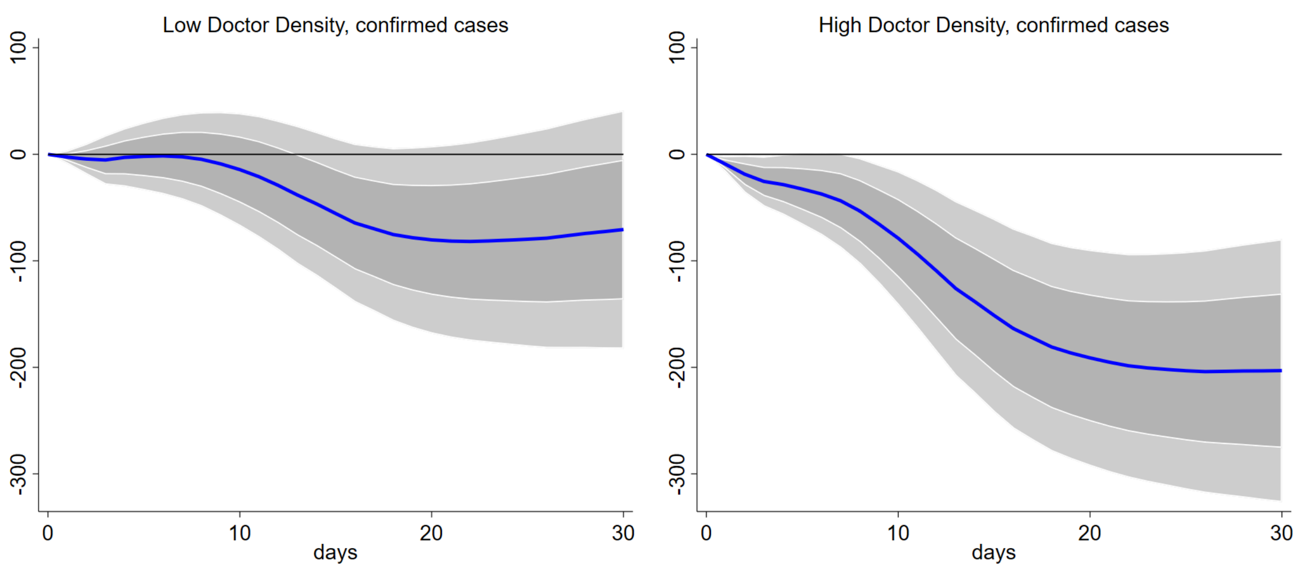
Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graphs show the cumulative response for cases and daily response for energy consumption growth with confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} \ = \ u_i + \mathrm{q}_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections or economic indicator in state i at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

Figure A2: Interaction with Health Infrastructure

Health Expenditure per Capita



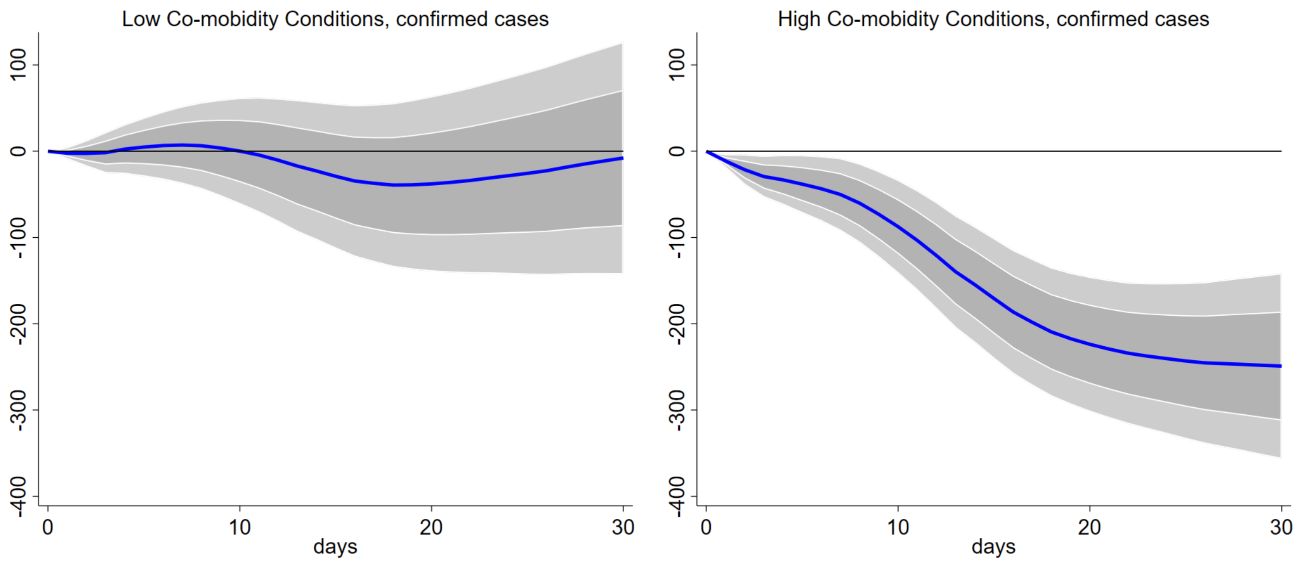
Doctor Density, number of doctors per 1000 people



Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the cumulative response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t})c_{i,t} + \theta_h^H(1 - F(z_{i,t}))c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell}\Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}}(1 - F(z_{i,t}))\psi_{h,\ell}\Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections in state i at date t. The model is estimated at each horizon $h = 0, 1, \ldots H$, with a lag structure $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

Figure A3: Interaction with Comorbidities

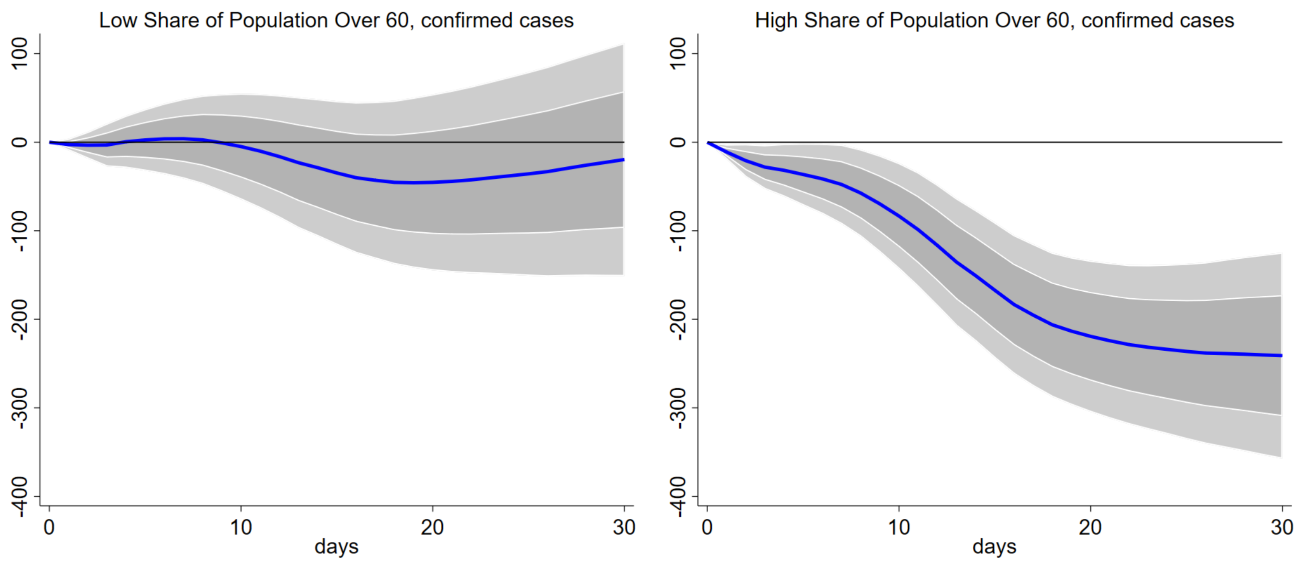
Prevalence of Diabetes Mellitus, Chronic Respiratory Diseases, Cardiovascular Diseases and Cancer



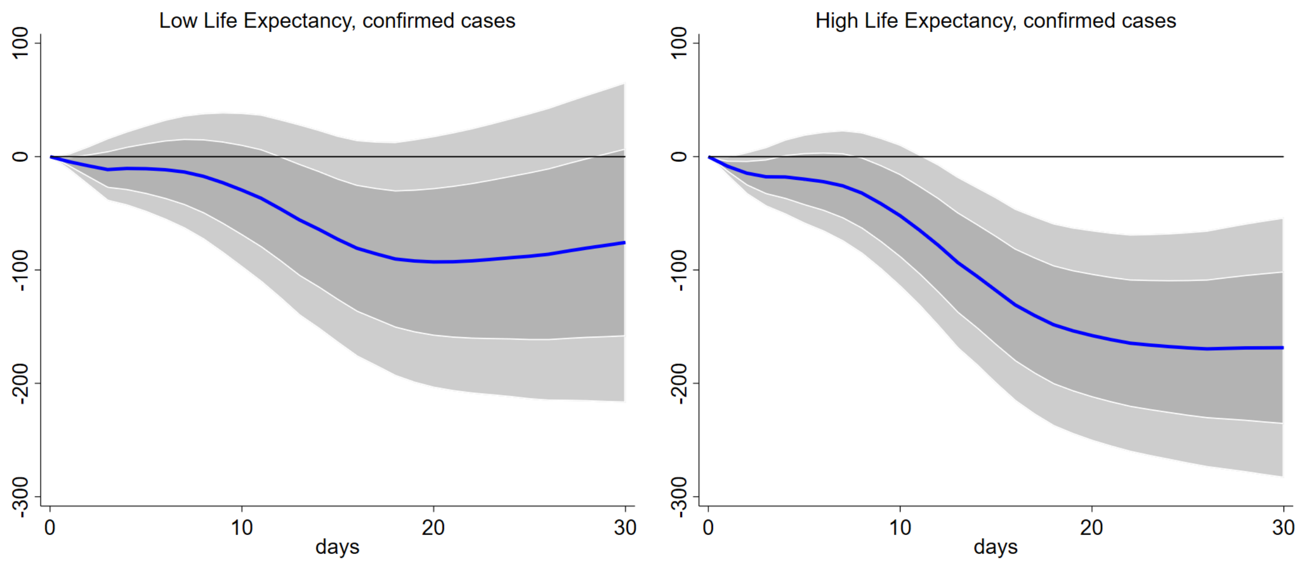
Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the cumulative response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t} \Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1 - exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections in state i at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

Figure A4: Interaction with Share of Population over 60 and Life Expectancy

Share of population over 60 years of Age



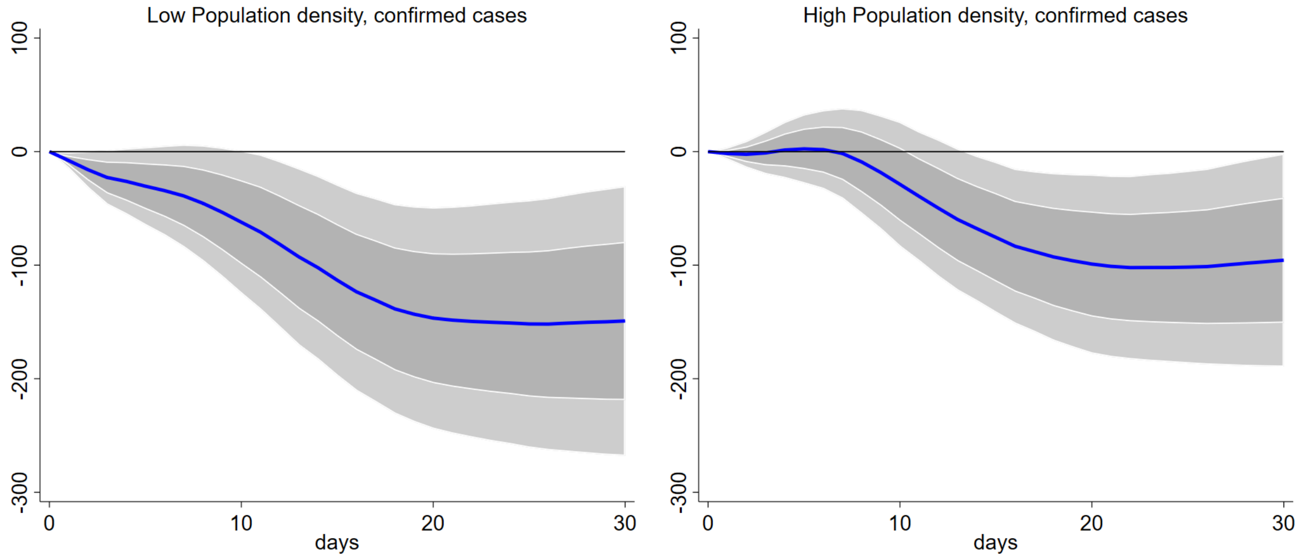
Life expectancy



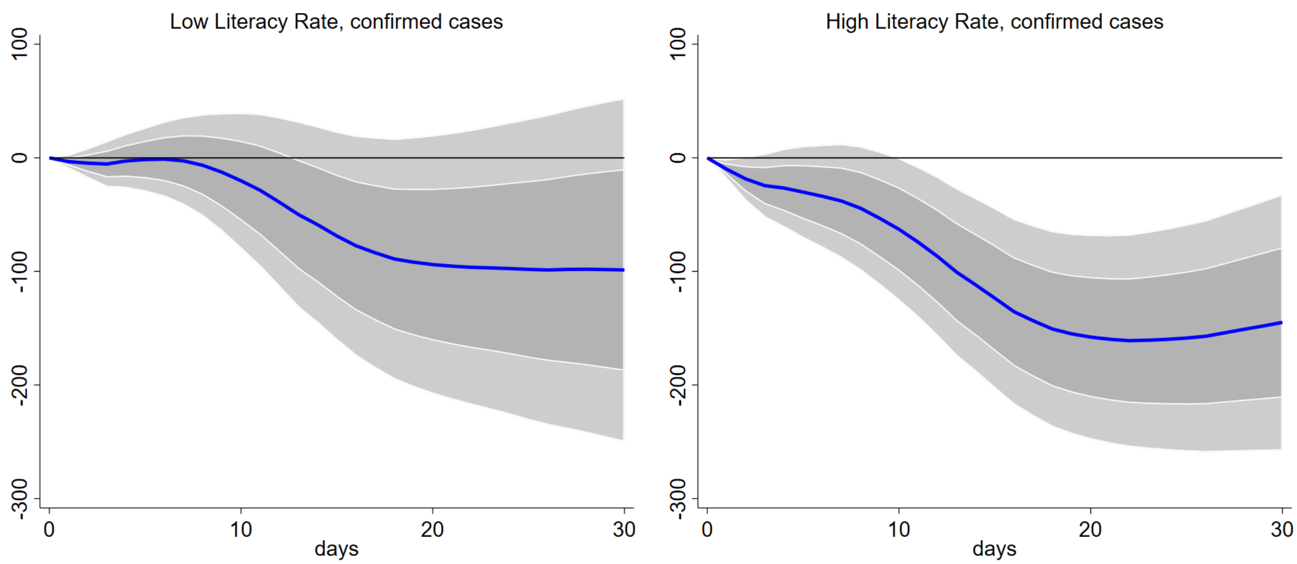
Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the cumulative response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections in state i at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

Figure A5: Interaction with Ease of Implementing Social Distancing

Population Density



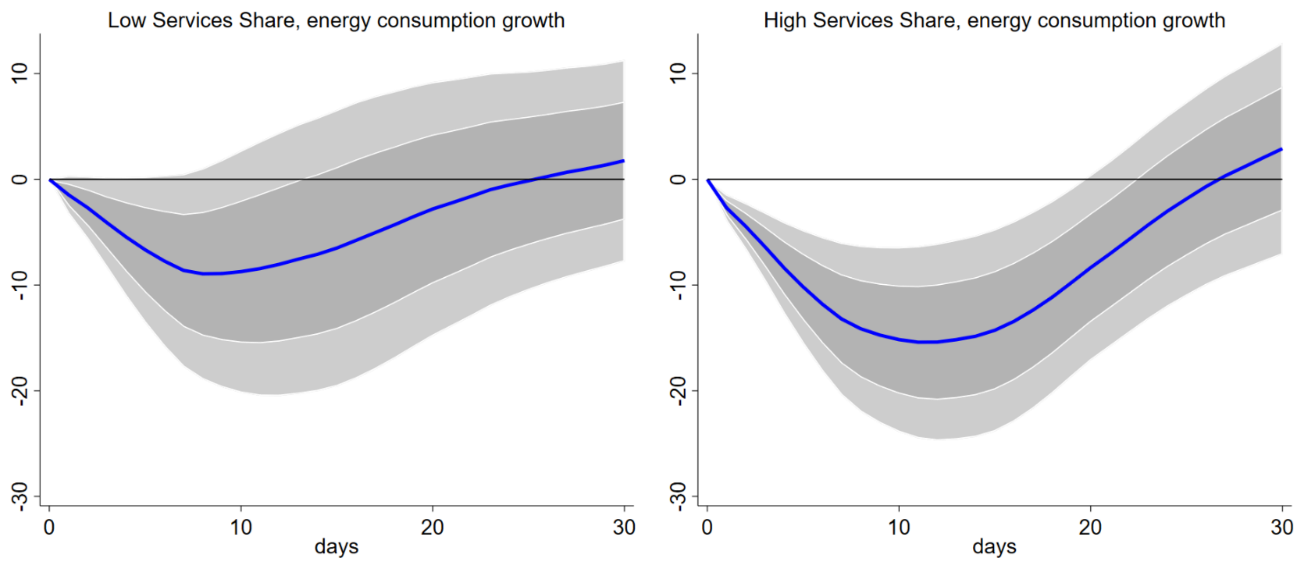
Literacy Rate



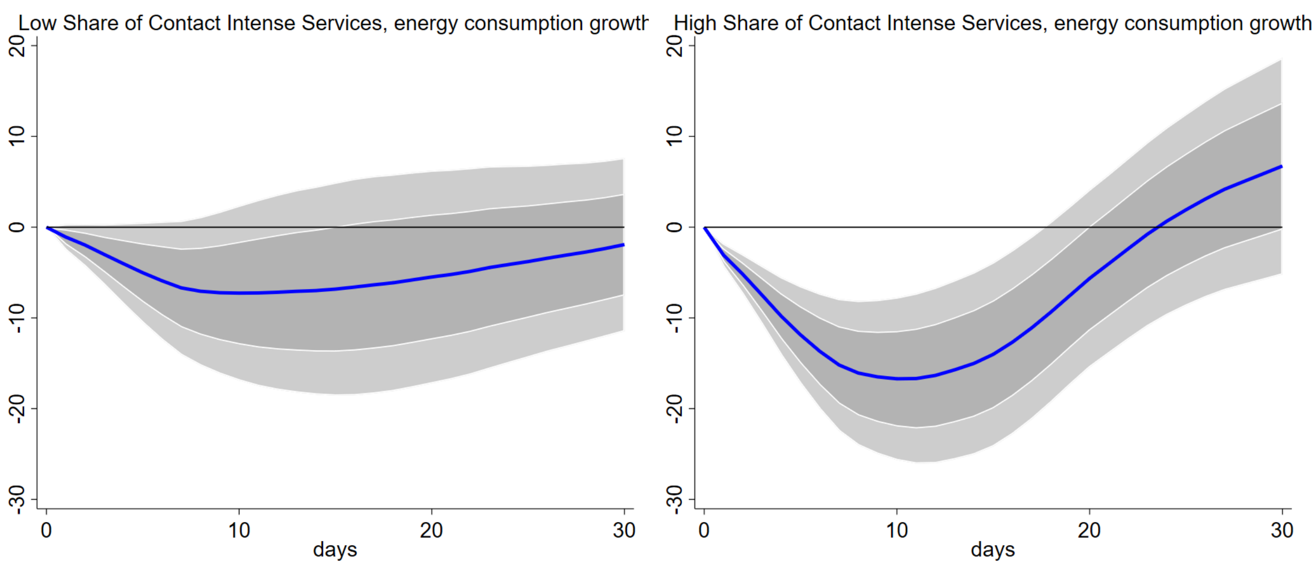
Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the cumulative response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t} \Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections in state i at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

Figure A6: Interaction with Share of Services

Services Share

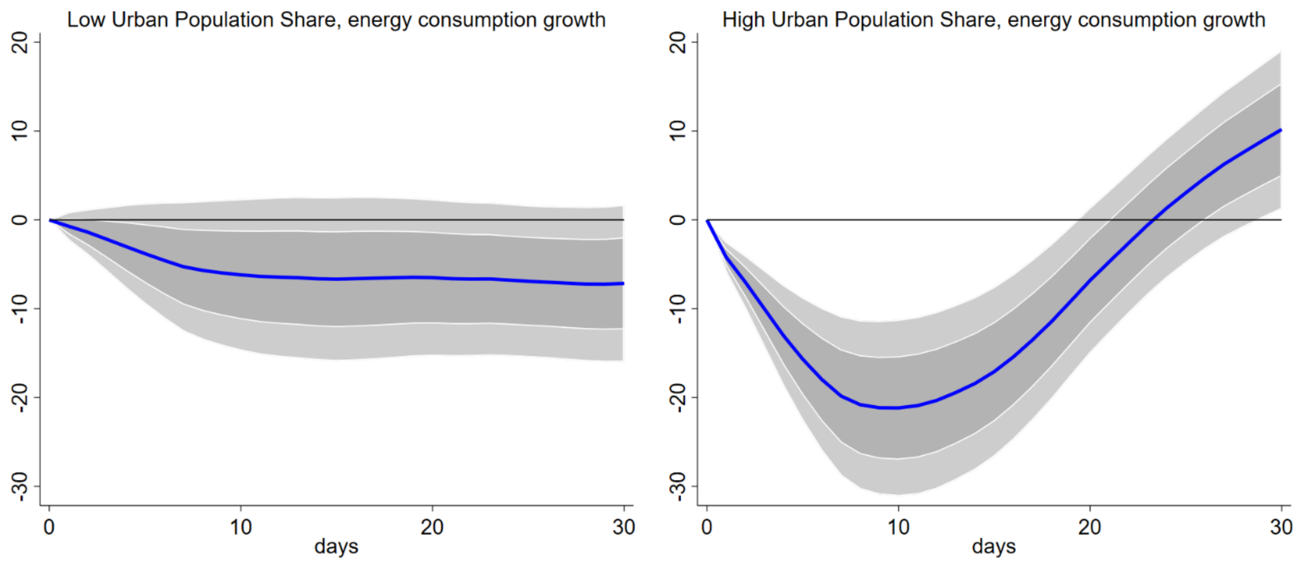


Contact-intensive Services Share



Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections in state i at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

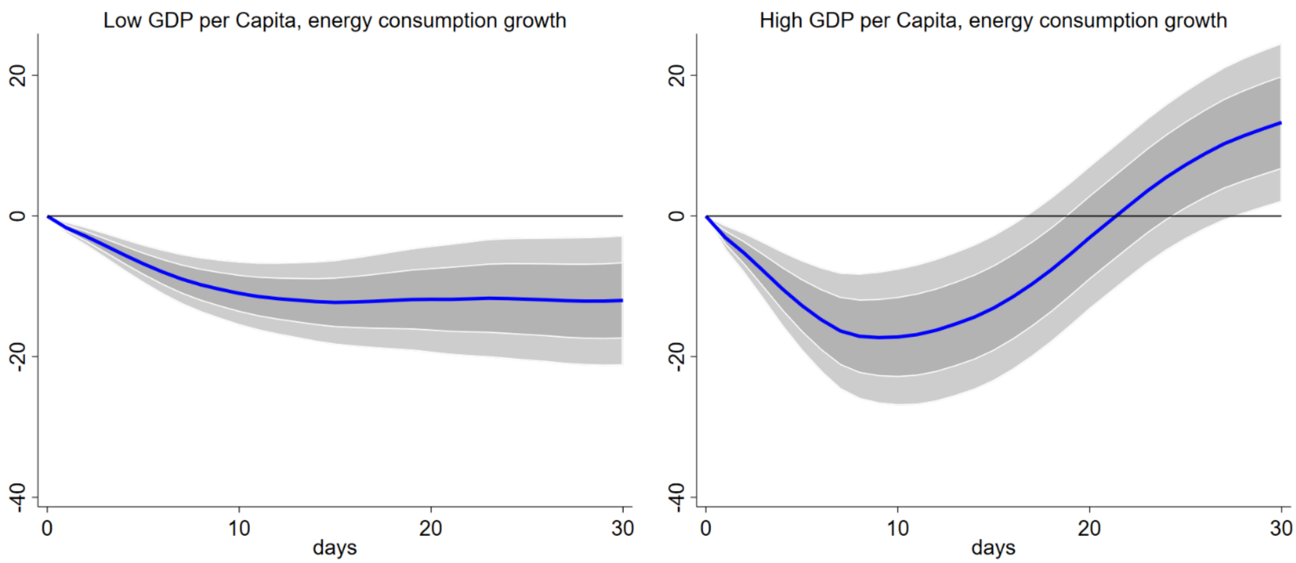
Figure A7: Interaction with Urbanization



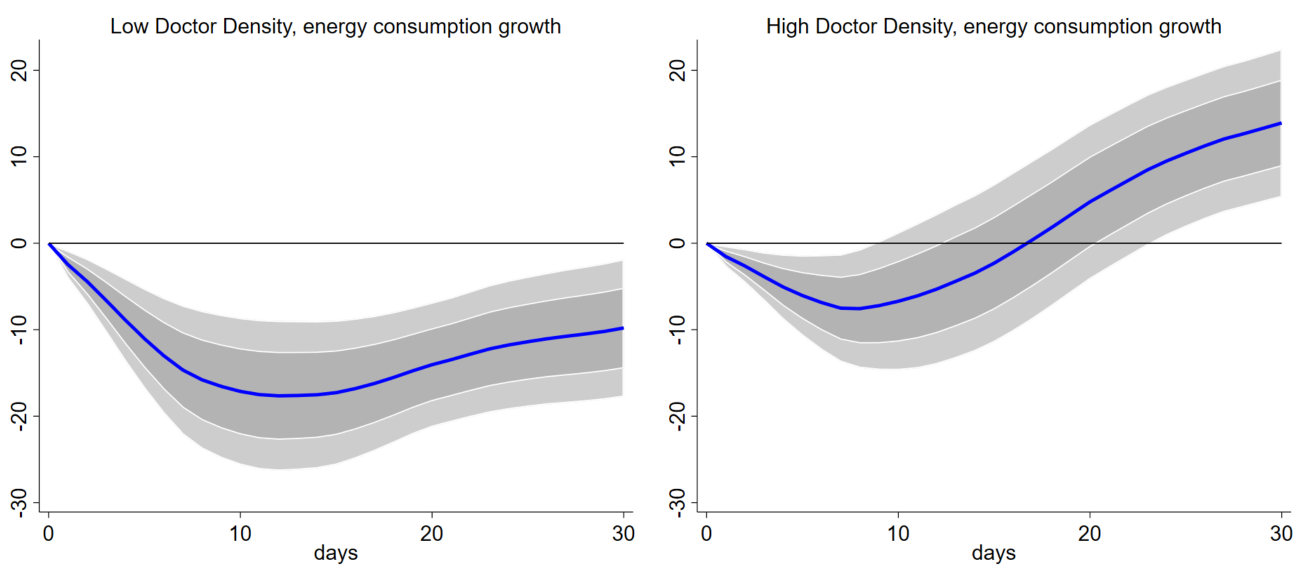
Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t})c_{i,t} + \theta_h^H(1 - F(z_{i,t}))c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\,\psi_{h,\ell}\Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}}(1 - F(z_{i,t}))\psi_{h,\ell}\Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections in state i at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

Figure A8: Interaction with income level and health infrastructure

State GDP per Capita

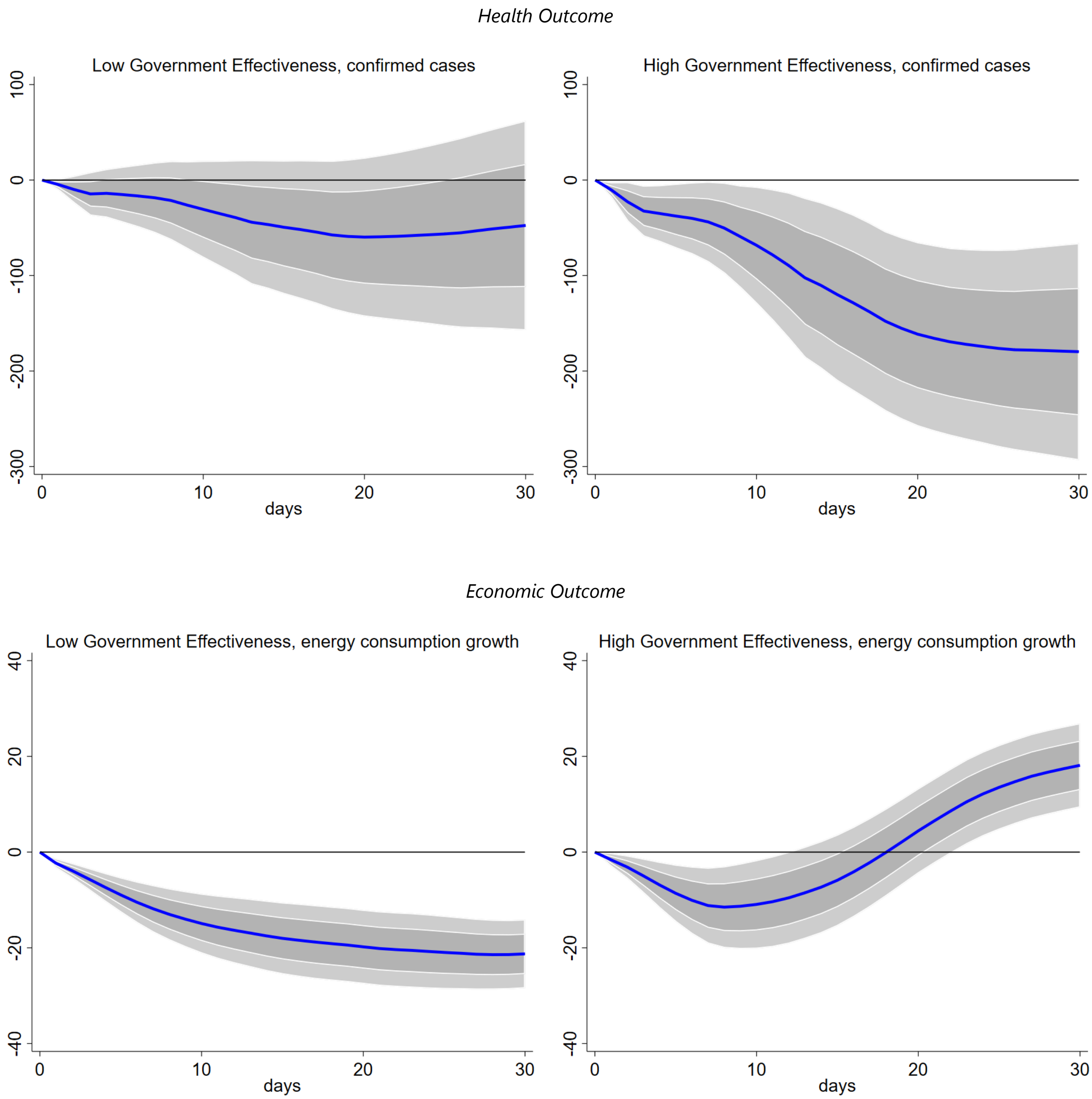


Doctor Density, number of doctors per 1000 people



Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t} \Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections in state i at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

Figure A9: Role of Government Effectiveness



Note: Impulse response functions are estimated using a sample of 34 states using daily data from February 15, 2020 to January 12, 2021. The graph shows the response and confidence bands at 95 and 75 percent. The horizontal axis shows the response x days after effective social distancing. Estimates based on $\Delta I_{i,t+h} = u_i + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t} \Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta I_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta I_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta I_{i,t+h} = I_{i,t+h} - I_{i,t+h-1}$ and $I_{i,t}$ is the log of the number of infections in state i at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the measure of effective state-level containment and social distancing; X is a matrix of time varying control variables and state specific time trend; and u_i captures state level fixed effects.

ANNEX TABLES

Table A1: Data Definitions and Sources

	Category	Definition	Source
Daily indicators	COVID indicators	Total confirmed COVID cases	CEIC
		Daily confirmed COVID cases	CEIC
	Economic indicators	Electricity consumption	POSOCO
		NO2 emissions	Air Quality Open Data Platform
		Flight (sum of daily departure and arrivals)	FlightRadar24
	Google mobility indicators	Google mobility- retail and receation	Google Mobility Report
		Google mobility- transit stations	Google Mobility Report
	National lockdown strigency	IMF Lockdown Strigency Index	Furceri, Kothari and Zhang (forthcoming)
		Oxford Strigency Index	Oxford University
Health infrastructure	Health expenditure	Health expenditure per capita	RBI: State Finances 2020-2021
	Doctor density	Doctors registered with State Medical Councils/Medical Council of India in 2016, per thousand	CMIE, CEIC, and IMF staff calculations
Vulnerable population	Population over 60	Share/percent of population in 60+ age cohort	RBI: State Finances 2020-2021
	Comorbidities	Prevalence of COVID-19 risk conditions in 2017- Diabetes Mellitus	RBI: State Finances 2020-2021
		Prevalence of COVID-19 risk conditions in 2017- Chronic Respiratory Diseases	RBI: State Finances 2020-2021
		Prevalence of COVID-19 risk conditions in 2017- Cardlo Vascular Diseases	RBI: State Finances 2020-2021
		Prevalence of COVID-19 risk conditions in 2017- Cancer	RBI: State Finances 2020-2021
	Life expectancy	Life expectancy in years	RBI: State Finances 2020-2021
Ease of social distancing	Population density	Population density per sq.km in 2011	Density of India State of Population Census 2011
	Literacy rate	Literacy rate in percent among persons of age 7 years and above	NSS Report No.585
Economic structure	GDP shares by sector	Percent of trade, hotels, transport, etc. in state of GDP	CMIE
		Percent of services in state GDP	CMIE
	Urbanization	Percentage of urban population to total population in 2001	Census of India Chapter IV: Trends in Urbanization
Income	State GDP per capita	State GDP per capita for 2018-19	RBI: State Finances 2020-2021
Governance	Government effectiveness	Governance ranking, average of average of ranks, actual data	National Institute of Public Finance and Policy: S. Mundle et. al. (2012)

Table A2: Cross-Correlations - State-Level Characteristics

		Health infrastructure		Vulnerable population			Ease of social distancing		Economic structure			Income	Governance
		Health Expenditure per capita	Doctor Density	Comorbidities	Share of 60+ population	Life expectancy	Population density	Literacy rate	Share of services	Share of contact-intensive services	Urbanisation	GDP per capita	Government effectiveness
Health infrastructure	Health Expenditure per capita	1.00											
	Doctor Density	0.40	1.00										
Vulnerable population	Comorbidities	0.46	0.79	1.00									
	Share of 60+ population	0.41	0.83	0.97	1.00								
	Life expectancy	0.12	0.64	0.77	0.85	1.00							
Ease of social distancing	Population density	-0.46	-0.07	0.10	0.16	0.32	1.00						
	Literacy rate	0.26	0.34	0.60	0.61	0.57	0.20	1.00					
Economic structure	Share of services	-0.01	0.48	0.56	0.59	0.64	0.68	0.45	1.00				
	Share of contact-intensive services	0.19	0.21	0.32	0.40	0.53	0.56	0.27	0.69	1.00			
	Urbanisation	0.28	0.71	0.85	0.84	0.75	-0.11	0.54	0.39	0.26	1.00		
Income	GDP per capita	0.46	0.60	0.74	0.69	0.63	-0.20	0.51	0.35	0.34	0.87	1.00	
Governance	Government effectiveness	0.64	0.71	0.73	0.65	0.42	-0.25	0.28	0.21	0.18	0.67	0.77	1.00

Table A3: Impact of Effective Social Distancing

(Underlying Regression Results for Figure 7)

Dependent Variable: Confirmed cases cumulative difference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	f1.ccase	f2.ccase	f3.ccase	f4.ccase	f5.ccase	f6.ccase	f7.ccase	f8.ccase	f9.ccase	f10.ccase
eli	-0.0535**	-0.0970**	-0.127*	-0.139*	-0.159*	-0.185*	-0.228**	-0.297**	-0.381***	-0.475***
	(0.0216)	(0.0469)	(0.0673)	(0.0767)	(0.0865)	(0.0948)	(0.105)	(0.116)	(0.132)	(0.150)
L.ccase	0.172***	0.285***	0.365***	0.421***	0.494***	0.556***	0.576***	0.609***	0.628***	0.615***
	(0.0278)	(0.0378)	(0.0547)	(0.0567)	(0.0664)	(0.0798)	(0.0888)	(0.0965)	(0.109)	(0.114)
L2.ccase	-0.0733**	-0.116***	-0.154***	-0.136**	-0.157**	-0.199***	-0.192**	-0.206***	-0.236***	-0.210***
	(0.0356)	(0.0378)	(0.0469)	(0.0518)	(0.0686)	(0.0634)	(0.0707)	(0.0717)	(0.0764)	(0.0751)
L3.ccase	-0.0710**	-0.119***	-0.113***	-0.151***	-0.196***	-0.202***	-0.216***	-0.245***	-0.227***	-0.239***
	(0.0305)	(0.0371)	(0.0369)	(0.0528)	(0.0472)	(0.0556)	(0.0560)	(0.0629)	(0.0642)	(0.0667)
L4.ccase	-0.0363	-0.0669*	-0.125***	-0.170***	-0.186***	-0.210***	-0.233***	-0.232***	-0.251***	-0.262**
	(0.0228)	(0.0341)	(0.0427)	(0.0592)	(0.0632)	(0.0689)	(0.0776)	(0.0819)	(0.0911)	(0.0982)
time	-5.93e-05	-0.000103	-0.000108	-8.37e-05	-7.74e-05	-7.56e-05	-0.000104	-0.000185	-0.000293	-0.000421
	(4.33e-05)	(9.60e-05)	(0.000148)	(0.000188)	(0.000229)	(0.000270)	(0.000313)	(0.000358)	(0.000408)	(0.000464)
Constant	1.438	2.538	2.765	2.348	2.329	2.419	3.181	5.141	7.688	10.70
	(0.963)	(2.134)	(3.276)	(4.163)	(5.060)	(5.967)	(6.898)	(7.898)	(8.998)	(10.23)
Observations	9,008	8,977	8,946	8,915	8,884	8,853	8,822	8,791	8,760	8,729
R-squared	0.211	0.316	0.366	0.401	0.426	0.446	0.460	0.474	0.488	0.500
Number of state	31	31	31	31	31	31	31	31	31	31

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	f11.ccase	f12.ccase	f13.ccase	f14.ccase	f15.ccase	f16.ccase	f17.ccase	f18.ccase	f19.ccase	f20.ccase
eli	-0.570***	-0.676***	-0.784***	-0.878***	-0.977***	-1.071***	-1.140***	-1.206***	-1.252***	-1.291***
	(0.165)	(0.180)	(0.194)	(0.199)	(0.207)	(0.213)	(0.218)	(0.222)	(0.226)	(0.230)
L.ccase	0.626***	0.623***	0.608***	0.600***	0.623***	0.610***	0.607***	0.597***	0.581***	0.554***
	(0.128)	(0.140)	(0.148)	(0.160)	(0.159)	(0.165)	(0.172)	(0.180)	(0.186)	(0.195)
L2.ccase	-0.222***	-0.228***	-0.222**	-0.195**	-0.233**	-0.232**	-0.236**	-0.242**	-0.244**	-0.224**
	(0.0774)	(0.0825)	(0.0834)	(0.0943)	(0.0936)	(0.0955)	(0.0958)	(0.0956)	(0.0956)	(0.0941)
L3.ccase	-0.247***	-0.243***	-0.217**	-0.248***	-0.248***	-0.248**	-0.256**	-0.260**	-0.244**	-0.240**
	(0.0738)	(0.0765)	(0.0881)	(0.0864)	(0.0898)	(0.0910)	(0.0956)	(0.0982)	(0.104)	(0.109)
L4.ccase	-0.262**	-0.267**	-0.294**	-0.291**	-0.284**	-0.283**	-0.275**	-0.264*	-0.269*	-0.275*
	(0.100)	(0.107)	(0.107)	(0.114)	(0.121)	(0.128)	(0.132)	(0.137)	(0.137)	(0.136)
time	-0.000556	-0.000716	-0.000878	-0.00103	-0.00120*	-0.00136*	-0.00148*	-0.00160*	-0.00169*	-0.00175*
	(0.000510)	(0.000557)	(0.000600)	(0.000640)	(0.000682)	(0.000723)	(0.000764)	(0.000805)	(0.000844)	(0.000885)
Constant	13.85	17.56	21.34	24.93*	28.73*	32.40*	35.30**	38.11**	40.08**	41.72**
	(11.25)	(12.29)	(13.24)	(14.11)	(15.03)	(15.95)	(16.85)	(17.73)	(18.61)	(19.50)
Observations	8,698	8,667	8,636	8,605	8,574	8,543	8,512	8,481	8,450	8,419
R-squared	0.512	0.524	0.536	0.549	0.561	0.573	0.583	0.592	0.600	0.609
Number of state	31	31	31	31	31	31	31	31	31	31

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
VARIABLES	f21.ccase	f22.ccase	f23.ccase	f24.ccase	f25.ccase	f26.ccase	f27.ccase	f28.ccase	f29.ccase	f30.ccase
eli	-1.318***	-1.337***	-1.351***	-1.364***	-1.377***	-1.386***	-1.386***	-1.387***	-1.388***	-1.387***
	(0.234)	(0.239)	(0.245)	(0.250)	(0.256)	(0.262)	(0.268)	(0.274)	(0.280)	(0.285)
L.ccase	0.546***	0.544***	0.526***	0.514***	0.495**	0.468**	0.464**	0.446**	0.417**	0.399**
	(0.194)	(0.190)	(0.187)	(0.185)	(0.188)	(0.184)	(0.176)	(0.170)	(0.168)	(0.166)
L2.ccase	-0.218**	-0.235**	-0.226**	-0.230**	-0.231**	-0.205**	-0.215**	-0.225**	-0.215**	-0.216**
	(0.0947)	(0.0944)	(0.0944)	(0.0938)	(0.0911)	(0.0907)	(0.0887)	(0.0882)	(0.0912)	(0.0917)
L3.ccase	-0.257**	-0.250**	-0.257**	-0.257**	-0.237**	-0.250**	-0.264**	-0.254**	-0.251**	-0.256**
	(0.108)	(0.108)	(0.107)	(0.110)	(0.115)	(0.114)	(0.111)	(0.111)	(0.114)	(0.115)
L4.ccase	-0.264*	-0.260*	-0.251*	-0.242*	-0.250*	-0.243*	-0.221	-0.212	-0.203	-0.186
	(0.137)	(0.139)	(0.143)	(0.142)	(0.140)	(0.142)	(0.143)	(0.144)	(0.147)	(0.147)
time	-0.00180*	-0.00183*	-0.00185*	-0.00188*	-0.00191*	-0.00193*	-0.00193*	-0.00193	-0.00194	-0.00193
	(0.000924)	(0.000964)	(0.00100)	(0.00103)	(0.00106)	(0.00109)	(0.00112)	(0.00115)	(0.00118)	(0.00120)
Constant	42.82**	43.55**	44.09*	44.87*	45.62*	46.26*	46.40*	46.51*	46.70*	46.69*
	(20.36)	(21.24)	(22.07)	(22.74)	(23.39)	(24.03)	(24.70)	(25.33)	(25.91)	(26.50)
Observations	8,388	8,357	8,326	8,295	8,264	8,234	8,203	8,172	8,141	8,110
R-squared	0.616	0.624	0.631	0.638	0.644	0.651	0.657	0.664	0.670	0.676
Number of state	31	31	31	31	31	31	31	31	31	31

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent Variable: Energy consumption growth difference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	f1d.en_gr	f2d.en_gr	f3d.en_gr	f4d.en_gr	f5d.en_gr	f6d.en_gr	f7d.en_gr	f8d.en_gr	f9d.en_gr	f10d.en_gr
eli	-0.0225***	-0.0386***	-0.0565***	-0.0744***	-0.0906***	-0.105***	-0.117***	-0.124***	-0.127***	-0.128***
	(0.00407)	(0.00641)	(0.00888)	(0.0113)	(0.0136)	(0.0155)	(0.0172)	(0.0185)	(0.0196)	(0.0205)
L.en_gr	0.928***	0.868***	0.799***	0.725***	0.652***	0.581***	0.515***	0.463***	0.420***	0.383***
	(0.00517)	(0.00890)	(0.0131)	(0.0174)	(0.0217)	(0.0258)	(0.0296)	(0.0323)	(0.0341)	(0.0358)
L2.en_gr	-0.929***	-0.869***	-0.801***	-0.727***	-0.654***	-0.583***	-0.517***	-0.465***	-0.423***	-0.386***
	(0.00514)	(0.00887)	(0.0130)	(0.0173)	(0.0216)	(0.0257)	(0.0296)	(0.0322)	(0.0340)	(0.0357)
time	2.28e-05*	4.72e-05**	7.71e-05***	0.000111***	0.000148***	0.000187***	0.000224***	0.000257***	0.000285***	0.000312***
	(1.18e-05)	(1.88e-05)	(2.63e-05)	(3.41e-05)	(4.16e-05)	(4.90e-05)	(5.57e-05)	(6.11e-05)	(6.56e-05)	(6.99e-05)
Constant	-0.504*	-1.044**	-1.703***	-2.455***	-3.278***	-4.123***	-4.947***	-5.672***	-6.308***	-6.900***
	(0.261)	(0.417)	(0.582)	(0.755)	(0.923)	(1.085)	(1.233)	(1.353)	(1.453)	(1.548)
Observations	10,558	10,526	10,494	10,462	10,430	10,398	10,366	10,334	10,302	10,270
R-squared	0.925	0.862	0.792	0.723	0.659	0.602	0.554	0.518	0.491	0.468
Number of state	32	32	32	32	32	32	32	32	32	32

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	f11d.en_gr	f12d.en_gr	f13d.en_gr	f14d.en_gr	f15d.en_gr	f16d.en_gr	f17d.en_gr	f18d.en_gr	f19d.en_gr	f20d.en_gr
eli	-0.127***	-0.125***	-0.121***	-0.117***	-0.111***	-0.103***	-0.0935***	-0.0834***	-0.0722***	-0.0612**
	(0.0213)	(0.0220)	(0.0226)	(0.0232)	(0.0239)	(0.0244)	(0.0249)	(0.0254)	(0.0259)	(0.0263)
L.en_gr	0.349***	0.321***	0.297***	0.274***	0.255***	0.241***	0.231***	0.224***	0.221***	0.218***
	(0.0374)	(0.0386)	(0.0393)	(0.0400)	(0.0402)	(0.0399)	(0.0393)	(0.0386)	(0.0378)	(0.0373)
L2.en_gr	-0.352***	-0.324***	-0.300***	-0.278***	-0.259***	-0.245***	-0.235***	-0.228***	-0.225***	-0.222***
	(0.0373)	(0.0385)	(0.0392)	(0.0399)	(0.0401)	(0.0397)	(0.0392)	(0.0384)	(0.0376)	(0.0371)
time	0.000337***	0.000361***	0.000383***	0.000404***	0.000425***	0.000443***	0.000460***	0.000475***	0.000488***	0.000499***
	(7.38e-05)	(7.71e-05)	(7.99e-05)	(8.24e-05)	(8.45e-05)	(8.60e-05)	(8.73e-05)	(8.82e-05)	(8.87e-05)	(8.93e-05)
Constant	-7.459***	-7.983***	-8.475***	-8.954***	-9.412***	-9.830***	-10.21***	-10.54***	-10.83***	-11.08***
	(1.634)	(1.707)	(1.768)	(1.824)	(1.870)	(1.905)	(1.932)	(1.952)	(1.965)	(1.977)
Observations	10,238	10,206	10,174	10,142	10,110	10,078	10,046	10,014	9,982	9,950
R-squared	0.450	0.435	0.423	0.413	0.405	0.399	0.396	0.394	0.394	0.395
Number of state	32	32	32	32	32	32	32	32	32	32

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
VARIABLES	f21d.en_gr	f22d.en_gr	f23d.en_gr	f24d.en_gr	f25d.en_gr	f26d.en_gr	f27d.en_gr	f28d.en_gr	f29d.en_gr	f30d.en_gr
eli	-0.0516*	-0.0415	-0.0313	-0.0224	-0.0144	-0.00661	0.000580	0.00663	0.0129	0.0195
	(0.0267)	(0.0270)	(0.0272)	(0.0274)	(0.0275)	(0.0277)	(0.0280)	(0.0281)	(0.0282)	(0.0283)
L.en_gr	0.213***	0.209***	0.206***	0.204***	0.201***	0.198***	0.194***	0.186***	0.177***	0.168***
	(0.0373)	(0.0376)	(0.0380)	(0.0388)	(0.0397)	(0.0408)	(0.0420)	(0.0431)	(0.0440)	(0.0446)
L2.en_gr	-0.218***	-0.213***	-0.211***	-0.208***	-0.205***	-0.202***	-0.198***	-0.191***	-0.182***	-0.173***
	(0.0371)	(0.0374)	(0.0378)	(0.0386)	(0.0396)	(0.0407)	(0.0419)	(0.0430)	(0.0439)	(0.0445)
time	0.000510***	0.000521***	0.000531***	0.000538***	0.000545***	0.000550***	0.000557***	0.000565***	0.000574***	0.000585***
	(9.04e-05)	(9.16e-05)	(9.28e-05)	(9.40e-05)	(9.53e-05)	(9.65e-05)	(9.79e-05)	(9.96e-05)	(0.000101)	(0.000103)
Constant	-11.34***	-11.59***	-11.80***	-11.97***	-12.12***	-12.25***	-12.40***	-12.58***	-12.79***	-13.04***
	(2.001)	(2.027)	(2.053)	(2.079)	(2.106)	(2.133)	(2.163)	(2.199)	(2.233)	(2.267)
Observations	9,918	9,886	9,854	9,822	9,790	9,759	9,727	9,695	9,663	9,631
R-squared	0.396	0.397	0.399	0.402	0.404	0.407	0.410	0.412	0.414	0.417
Number of state	32	32	32	32	32	32	32	32	32	32

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Impact of Effective Social Distancing on other proxies for economic activity

(Underlying Regression Results for Figure 8)

Dependent Variable: NO2 Emissions cumulative difference

VARIABLES	(1) f1.n	(2) f2.n	(3) f3.n	(4) f4.n	(5) f5.n	(6) f6.n	(7) f7.n	(8) f8.n	(9) f9.n	(10) f10.n
eli	-0.0384***	-0.105***	-0.201***	-0.326***	-0.478***	-0.657***	-0.851***	-1.049***	-1.241***	-1.427***
	(0.0111)	(0.0289)	(0.0543)	(0.0878)	(0.128)	(0.175)	(0.227)	(0.283)	(0.341)	(0.403)
L.n	0.955***	1.875***	2.754***	3.593***	4.390***	5.148***	5.871***	6.570***	7.252***	7.920***
	(0.00608)	(0.0175)	(0.0352)	(0.0596)	(0.0901)	(0.126)	(0.167)	(0.211)	(0.258)	(0.307)
L2.n	-0.955***	-1.874***	-2.754***	-3.593***	-4.390***	-5.147***	-5.870***	-6.569***	-7.250***	-7.918***
	(0.00615)	(0.0177)	(0.0355)	(0.0601)	(0.0908)	(0.127)	(0.168)	(0.213)	(0.259)	(0.308)
time	0.000154	0.000365	0.000619	0.000906	0.00122	0.00156	0.00196	0.00242	0.00298	0.00373
	(0.000185)	(0.000468)	(0.000850)	(0.00133)	(0.00191)	(0.00256)	(0.00328)	(0.00404)	(0.00487)	(0.00570)
Constant	-3.309	-7.797	-13.18	-19.18	-25.69	-32.74	-41.00	-50.73	-62.38	-78.50
	(4.069)	(10.30)	(18.74)	(29.41)	(42.10)	(56.52)	(72.28)	(89.16)	(107.3)	(125.7)
Observations	4,957	4,942	4,927	4,912	4,897	4,882	4,867	4,852	4,837	4,822
R-squared	0.960	0.945	0.929	0.913	0.897	0.882	0.868	0.855	0.845	0.836
Number of state	15	15	15	15	15	15	15	15	15	15

VARIABLES	(11) f11.n	(12) f12.n	(13) f13.n	(14) f14.n	(15) f15.n	(16) f16.n	(17) f17.n	(18) f18.n	(19) f19.n	(20) f20.n
eli	-1.599***	-1.756***	-1.893***	-2.007***	-2.101**	-2.170**	-2.215**	-2.245**	-2.260*	-2.264*
	(0.467)	(0.533)	(0.602)	(0.674)	(0.750)	(0.833)	(0.922)	(1.014)	(1.110)	(1.210)
L.n	8.579***	9.232***	9.881***	10.53***	11.19***	11.84***	12.49***	13.14***	13.79***	14.43***
	(0.357)	(0.407)	(0.459)	(0.512)	(0.566)	(0.622)	(0.677)	(0.731)	(0.783)	(0.832)
L2.n	-8.577***	-9.230***	-9.879***	-10.53***	-11.18***	-11.84***	-12.49***	-13.14***	-13.79***	-14.43***
	(0.359)	(0.410)	(0.462)	(0.515)	(0.569)	(0.626)	(0.681)	(0.736)	(0.788)	(0.838)
time	0.00461	0.00563	0.00678	0.00822	0.00981	0.0116	0.0136	0.0158	0.0184	0.0212
	(0.00659)	(0.00753)	(0.00855)	(0.00957)	(0.0107)	(0.0119)	(0.0132)	(0.0145)	(0.0159)	(0.0173)
Constant	-97.29	-119.0	-143.9	-175.1	-209.4	-247.5	-291.6	-340.3	-396.0	-458.3
	(145.2)	(166.0)	(188.3)	(210.8)	(235.0)	(261.9)	(289.7)	(319.0)	(349.3)	(381.0)
Observations	4,807	4,792	4,777	4,762	4,747	4,732	4,717	4,702	4,687	4,672
R-squared	0.829	0.822	0.817	0.812	0.809	0.805	0.802	0.800	0.798	0.795
Number of state	15	15	15	15	15	15	15	15	15	15

VARIABLES	(21) f21.n	(22) f22.n	(23) f23.n	(24) f24.n	(25) f25.n	(26) f26.n	(27) f27.n	(28) f28.n	(29) f29.n	(30) f30.n
eli	-2.268	-2.267	-2.264	-2.275	-2.306	-2.360	-2.429	-2.512	-2.599	-2.683
	(1.318)	(1.431)	(1.550)	(1.668)	(1.789)	(1.915)	(2.044)	(2.173)	(2.301)	(2.428)
L.n	15.05***	15.66***	16.26***	16.82***	17.36***	17.87***	18.36***	18.83***	19.30***	19.76***
	(0.884)	(0.938)	(0.993)	(1.049)	(1.110)	(1.177)	(1.246)	(1.313)	(1.375)	(1.434)
L2.n	-15.05***	-15.66***	-16.26***	-16.83***	-17.36***	-17.87***	-18.36***	-18.84***	-19.30***	-19.76***
	(0.890)	(0.945)	(1.001)	(1.058)	(1.120)	(1.188)	(1.257)	(1.325)	(1.388)	(1.447)
time	0.0243	0.0276	0.0311	0.0348	0.0385	0.0421	0.0457	0.0490	0.0523	0.0556
	(0.0188)	(0.0205)	(0.0223)	(0.0241)	(0.0260)	(0.0281)	(0.0301)	(0.0321)	(0.0340)	(0.0359)
Constant	-524.8	-596.4	-674.1	-755.2	-836.3	-914.7	-991.2	-1,064	-1,137	-1,208
	(415.0)	(452.0)	(491.6)	(531.9)	(573.8)	(617.9)	(663.0)	(706.9)	(749.1)	(790.5)
Observations	4,657	4,642	4,627	4,612	4,597	4,582	4,567	4,552	4,537	4,522
R-squared	0.793	0.790	0.788	0.785	0.782	0.778	0.775	0.771	0.768	0.765
Number of state	15	15	15	15	15	15	15	15	15	15

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent Variable: Total flights difference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	f1d.f	f2d.f	f3d.f	f4d.f	f5d.f	f6d.f	f7d.f	f8d.f	f9d.f	f10d.f
eli	-0.308***	-0.485***	-0.666***	-0.841***	-1.000***	-1.141***	-1.259***	-1.330***	-1.380***	-1.410***
	(0.0501)	(0.0779)	(0.106)	(0.133)	(0.158)	(0.179)	(0.196)	(0.205)	(0.212)	(0.216)
L.f	0.925***	0.878***	0.827***	0.774***	0.722***	0.672***	0.625***	0.585***	0.548***	0.515***
	(0.00923)	(0.0143)	(0.0194)	(0.0243)	(0.0288)	(0.0326)	(0.0357)	(0.0373)	(0.0384)	(0.0392)
L2.f	-0.925***	-0.878***	-0.827***	-0.774***	-0.722***	-0.672***	-0.625***	-0.585***	-0.548***	-0.514***
	(0.00921)	(0.0142)	(0.0194)	(0.0243)	(0.0287)	(0.0325)	(0.0356)	(0.0372)	(0.0383)	(0.0391)
time	0.000272*	0.000410*	0.000548*	0.000687*	0.000828*	0.000975*	0.00113*	0.00129*	0.00146*	0.00163*
	(0.000152)	(0.000230)	(0.000311)	(0.000391)	(0.000469)	(0.000545)	(0.000618)	(0.000684)	(0.000748)	(0.000809)
Constant	-5.640*	-8.463	-11.27	-14.11	-17.00	-20.02	-23.16*	-26.64*	-30.24*	-33.93*
	(3.298)	(5.007)	(6.747)	(8.484)	(10.19)	(11.84)	(13.44)	(14.89)	(16.29)	(17.62)
Observations	9,559	9,530	9,501	9,472	9,443	9,414	9,385	9,356	9,327	9,298
R-squared	0.982	0.965	0.946	0.924	0.900	0.876	0.850	0.823	0.797	0.770
Number of state	29	29	29	29	29	29	29	29	29	29

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	f11d.f	f12d.f	f13d.f	f14d.f	f15d.f	f16d.f	f17d.f	f18d.f	f19d.f	f20d.f
eli	-1.426***	-1.430***	-1.424***	-1.412***	-1.392***	-1.369***	-1.339***	-1.303***	-1.260***	-1.208***
	(0.219)	(0.222)	(0.224)	(0.225)	(0.226)	(0.226)	(0.226)	(0.224)	(0.222)	(0.219)
L.f	0.483***	0.453***	0.424***	0.396***	0.369***	0.342***	0.316***	0.291***	0.267***	0.244***
	(0.0397)	(0.0400)	(0.0403)	(0.0404)	(0.0405)	(0.0405)	(0.0404)	(0.0403)	(0.0400)	(0.0395)
L2.f	-0.483***	-0.452***	-0.424***	-0.396***	-0.369***	-0.342***	-0.316***	-0.291***	-0.266***	-0.244***
	(0.0395)	(0.0399)	(0.0402)	(0.0403)	(0.0403)	(0.0403)	(0.0403)	(0.0401)	(0.0398)	(0.0393)
time	0.00180**	0.00198**	0.00215**	0.00232**	0.00249**	0.00266**	0.00283**	0.00299**	0.00316**	0.00332**
	(0.000868)	(0.000926)	(0.000982)	(0.00104)	(0.00109)	(0.00114)	(0.00120)	(0.00125)	(0.00130)	(0.00134)
Constant	-37.66*	-41.38**	-45.14**	-48.83**	-52.53**	-56.21**	-59.85**	-63.45**	-67.04**	-70.61**
	(18.92)	(20.19)	(21.43)	(22.65)	(23.84)	(25.01)	(26.16)	(27.27)	(28.36)	(29.40)
Observations	9,269	9,240	9,211	9,182	9,153	9,124	9,095	9,066	9,037	9,008
R-squared	0.743	0.716	0.691	0.666	0.642	0.619	0.598	0.578	0.559	0.542
Number of state	29	29	29	29	29	29	29	29	29	29

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
VARIABLES	f21d.f	f22d.f	f23d.f	f24d.f	f25d.f	f26d.f	f27d.f	f28d.f	f29d.f	f30d.f
eli	-1.154***	-1.092***	-1.024***	-0.948***	-0.870***	-0.790***	-0.705***	-0.622***	-0.538**	-0.455**
	(0.216)	(0.212)	(0.208)	(0.205)	(0.202)	(0.199)	(0.197)	(0.197)	(0.196)	(0.196)
L.f	0.222***	0.201***	0.181***	0.162***	0.144***	0.127***	0.111***	0.0937**	0.0769**	0.0599*
	(0.0389)	(0.0382)	(0.0375)	(0.0368)	(0.0360)	(0.0354)	(0.0347)	(0.0342)	(0.0337)	(0.0333)
L2.f	-0.221***	-0.200***	-0.180***	-0.162***	-0.144***	-0.127***	-0.110***	-0.0929**	-0.0761**	-0.0591*
	(0.0387)	(0.0381)	(0.0373)	(0.0366)	(0.0359)	(0.0352)	(0.0346)	(0.0341)	(0.0336)	(0.0332)
time	0.00348**	0.00364**	0.00379**	0.00394**	0.00409**	0.00423**	0.00437**	0.00449**	0.00462**	0.00473**
	(0.00139)	(0.00143)	(0.00148)	(0.00152)	(0.00156)	(0.00160)	(0.00163)	(0.00167)	(0.00171)	(0.00174)
Constant	-74.11**	-77.59**	-81.01**	-84.35**	-87.58**	-90.70**	-93.68**	-96.50**	-99.22**	-101.8**
	(30.42)	(31.41)	(32.37)	(33.29)	(34.18)	(35.03)	(35.88)	(36.71)	(37.52)	(38.30)
Observations	8,979	8,950	8,921	8,892	8,863	8,835	8,806	8,777	8,748	8,719
R-squared	0.527	0.514	0.502	0.494	0.487	0.483	0.481	0.482	0.485	0.490
Number of state	29	29	29	29	29	29	29	29	29	29

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A5: Interaction with Health Infrastructure
(Underlying Regression Results for Figure A2)

Dependent Variable: confirmed cases cumulative difference - interaction with high and low doctor density

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	f1.ccase	f2.ccase	f3.ccase	f4.ccase	f5.ccase	f6.ccase	f7.ccase	f8.ccase	f9.ccase	f10.ccase
c.dh#c.eli (High)	-0.0927**	-0.187**	-0.255**	-0.284*	-0.326*	-0.372*	-0.436*	-0.532**	-0.656**	-0.788**
	(0.0389)	(0.0888)	(0.119)	(0.144)	(0.171)	(0.197)	(0.226)	(0.254)	(0.285)	(0.320)
c.dl#c.eli (Low)	-0.0261	-0.0441	-0.0529	-0.0288	-0.0194	-0.0152	-0.0234	-0.0471	-0.0895	-0.144
	(0.0316)	(0.0732)	(0.118)	(0.140)	(0.162)	(0.183)	(0.204)	(0.225)	(0.248)	(0.270)
L.ccase	0.198***	0.320***	0.398***	0.442***	0.513***	0.562***	0.586***	0.619***	0.645***	0.630***
	(0.0378)	(0.0527)	(0.0797)	(0.0798)	(0.0925)	(0.116)	(0.126)	(0.139)	(0.156)	(0.157)
L2.ccase	-0.0973**	-0.148***	-0.199***	-0.161**	-0.188***	-0.204***	-0.200**	-0.200**	-0.236**	-0.198**
	(0.0461)	(0.0448)	(0.0503)	(0.0600)	(0.0633)	(0.0694)	(0.0743)	(0.0779)	(0.0850)	(0.0842)
L3.ccase	-0.0856**	-0.158***	-0.137**	-0.193***	-0.220***	-0.237***	-0.240***	-0.281***	-0.254***	-0.267***
	(0.0358)	(0.0399)	(0.0510)	(0.0555)	(0.0622)	(0.0669)	(0.0687)	(0.0832)	(0.0792)	(0.0840)
L4.ccase	-0.0242	-0.0330	-0.0905	-0.126*	-0.152*	-0.178*	-0.213*	-0.215*	-0.242*	-0.262*
	(0.0309)	(0.0395)	(0.0561)	(0.0721)	(0.0815)	(0.0907)	(0.106)	(0.109)	(0.122)	(0.133)
time	-6.31e-05	-0.000123	-0.000138	-0.000103	-9.93e-05	-9.96e-05	-0.000128	-0.000206	-0.000324	-0.000466
	(5.72e-05)	(0.000133)	(0.000204)	(0.000257)	(0.000309)	(0.000358)	(0.000408)	(0.000457)	(0.000507)	(0.000558)
Constant	1.535	3.005	3.490	2.846	2.881	3.020	3.787	5.678	8.461	11.76
	(1.273)	(2.960)	(4.538)	(5.692)	(6.831)	(7.911)	(9.011)	(10.08)	(11.19)	(12.32)
Observations	6,706	6,683	6,660	6,637	6,614	6,591	6,568	6,545	6,522	6,499
R-squared	0.272	0.407	0.461	0.497	0.522	0.543	0.559	0.575	0.590	0.602
Number of state	23	23	23	23	23	23	23	23	23	23

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	f11.ccase	f12.ccase	f13.ccase	f14.ccase	f15.ccase	f16.ccase	f17.ccase	f18.ccase	f19.ccase	f20.ccase
c.dh#c.eli (High)	-0.937**	-1.095***	-1.260***	-1.383***	-1.512***	-1.635***	-1.723***	-1.809***	-1.865***	-1.911***
	(0.355)	(0.388)	(0.419)	(0.440)	(0.463)	(0.479)	(0.490)	(0.499)	(0.508)	(0.517)
c.dl#c.eli (Low)	-0.210	-0.291	-0.382	-0.465	-0.556	-0.645	-0.699*	-0.753*	-0.783*	-0.803*
	(0.291)	(0.310)	(0.331)	(0.344)	(0.361)	(0.379)	(0.395)	(0.414)	(0.432)	(0.448)
L.ccase	0.651***	0.646***	0.623***	0.633***	0.669***	0.675***	0.684***	0.682***	0.679***	0.667***
	(0.176)	(0.192)	(0.196)	(0.209)	(0.194)	(0.196)	(0.196)	(0.201)	(0.200)	(0.205)
L2.ccase	-0.216**	-0.222**	-0.195*	-0.172	-0.210*	-0.218*	-0.230*	-0.234*	-0.241*	-0.233*
	(0.0864)	(0.0933)	(0.0974)	(0.114)	(0.114)	(0.115)	(0.115)	(0.115)	(0.119)	(0.121)
L3.ccase	-0.281***	-0.257**	-0.231*	-0.265**	-0.273**	-0.283**	-0.290**	-0.297**	-0.291**	-0.295**
	(0.0985)	(0.0999)	(0.123)	(0.115)	(0.118)	(0.115)	(0.121)	(0.123)	(0.128)	(0.128)
L4.ccase	-0.261*	-0.284*	-0.323**	-0.330**	-0.327**	-0.323*	-0.321*	-0.314*	-0.317*	-0.315*
	(0.130)	(0.138)	(0.134)	(0.145)	(0.152)	(0.160)	(0.163)	(0.172)	(0.175)	(0.180)
time	-0.000641	-0.000846	-0.00107	-0.00128*	-0.00149*	-0.00171**	-0.00187**	-0.00204**	-0.00216**	-0.00226**
	(0.000607)	(0.000653)	(0.000699)	(0.000736)	(0.000774)	(0.000811)	(0.000843)	(0.000874)	(0.000902)	(0.000927)
Constant	15.82	20.53	25.64	30.38*	35.35*	40.25**	44.05**	47.84**	50.61**	53.05**
	(13.39)	(14.41)	(15.43)	(16.24)	(17.09)	(17.91)	(18.60)	(19.28)	(19.90)	(20.45)
Observations	6,476	6,453	6,430	6,407	6,384	6,361	6,338	6,315	6,292	6,269
R-squared	0.614	0.627	0.639	0.652	0.664	0.675	0.684	0.691	0.698	0.703
Number of state	23	23	23	23	23	23	23	23	23	23

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
VARIABLES	f21.ccase	f22.ccase	f23.ccase	f24.ccase	f25.ccase	f26.ccase	f27.ccase	f28.ccase	f29.ccase	f30.ccase
c.dh#c.eli (High)	-1.951***	-1.985***	-2.005***	-2.019***	-2.032***	-2.040***	-2.037***	-2.034***	-2.033***	-2.031***
	(0.527)	(0.535)	(0.546)	(0.557)	(0.569)	(0.581)	(0.594)	(0.606)	(0.618)	(0.630)
c.dl#c.eli (Low)	-0.815*	-0.818*	-0.813	-0.805	-0.797	-0.787	-0.765	-0.743	-0.726	-0.706
	(0.462)	(0.475)	(0.488)	(0.500)	(0.514)	(0.526)	(0.538)	(0.549)	(0.560)	(0.570)
L.ccase	0.667***	0.660***	0.633***	0.624***	0.615***	0.583***	0.557***	0.530**	0.495**	0.477**
	(0.200)	(0.200)	(0.198)	(0.194)	(0.194)	(0.194)	(0.189)	(0.189)	(0.188)	(0.185)
L2.ccase	-0.242*	-0.258*	-0.238*	-0.240*	-0.262**	-0.257*	-0.255*	-0.262*	-0.246*	-0.254*
	(0.123)	(0.124)	(0.126)	(0.126)	(0.126)	(0.127)	(0.129)	(0.130)	(0.134)	(0.134)
L3.ccase	-0.313**	-0.297**	-0.299**	-0.315**	-0.306**	-0.300**	-0.303**	-0.283**	-0.283**	-0.284*
	(0.130)	(0.132)	(0.131)	(0.130)	(0.132)	(0.131)	(0.133)	(0.136)	(0.136)	(0.139)
L4.ccase	-0.296	-0.295	-0.293	-0.272	-0.257	-0.243	-0.223	-0.216	-0.202	-0.182
	(0.185)	(0.188)	(0.191)	(0.195)	(0.195)	(0.200)	(0.204)	(0.207)	(0.213)	(0.216)
time	-0.00235**	-0.00243**	-0.00248**	-0.00253**	-0.00258**	-0.00262**	-0.00263**	-0.00264**	-0.00266**	-0.00267**
	(0.000949)	(0.000970)	(0.000991)	(0.00101)	(0.00104)	(0.00106)	(0.00109)	(0.00111)	(0.00114)	(0.00116)
Constant	55.15**	56.92**	58.21**	59.40**	60.47**	61.45**	61.89**	62.23**	62.69**	63.01**
	(20.94)	(21.40)	(21.88)	(22.37)	(22.91)	(23.45)	(24.00)	(24.54)	(25.09)	(25.62)
Observations	6,246	6,223	6,200	6,177	6,154	6,132	6,109	6,086	6,063	6,040
R-squared	0.709	0.714	0.718	0.723	0.728	0.733	0.737	0.742	0.747	0.753
Number of state	23	23	23	23	23	23	23	23	23	23

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A6: Interaction with Share of Services

(Underlying Regression Results for Figure A6)

Dependent Variable: energy consumption growth percentage points - interaction with high and low share of services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	f1d.en_gr	f2d.en_gr	f3d.en_gr	f4d.en_gr	f5d.en_gr	f6d.en_gr	f7d.en_gr	f8d.en_gr	f9d.en_gr	f10d.en_gr
c.dh#c.eli (High)	-0.0268***	-0.0444***	-0.0636***	-0.0837***	-0.102***	-0.118***	-0.132***	-0.141***	-0.147***	-0.152***
	(0.00640)	(0.0112)	(0.0165)	(0.0221)	(0.0274)	(0.0324)	(0.0368)	(0.0400)	(0.0424)	(0.0445)
c.dl#c.eli (Low)	-0.0146	-0.0269*	-0.0409*	-0.0544*	-0.0666*	-0.0773*	-0.0862*	-0.0894*	-0.0892	-0.0873
	(0.00916)	(0.0152)	(0.0217)	(0.0287)	(0.0352)	(0.0413)	(0.0465)	(0.0509)	(0.0548)	(0.0584)
L.en_gr	0.928***	0.867***	0.797***	0.721***	0.646***	0.573***	0.505***	0.452***	0.408***	0.370***
	(0.00576)	(0.00986)	(0.0143)	(0.0188)	(0.0232)	(0.0274)	(0.0313)	(0.0339)	(0.0356)	(0.0373)
L2.en_gr	-0.929***	-0.868***	-0.798***	-0.723***	-0.648***	-0.575***	-0.508***	-0.454***	-0.411***	-0.373***
	(0.00574)	(0.00984)	(0.0143)	(0.0188)	(0.0232)	(0.0274)	(0.0312)	(0.0338)	(0.0356)	(0.0372)
time	2.54e-05**	5.17e-05**	8.35e-05***	0.000120***	0.000159***	0.000199***	0.000239***	0.000273***	0.000302***	0.000330***
	(1.20e-05)	(1.90e-05)	(2.62e-05)	(3.38e-05)	(4.11e-05)	(4.81e-05)	(5.44e-05)	(5.95e-05)	(6.38e-05)	(6.78e-05)
Constant	-0.562**	-1.142**	-1.845***	-2.644***	-3.513***	-4.402***	-5.267***	-6.023***	-6.682***	-7.295***
	(0.266)	(0.420)	(0.581)	(0.749)	(0.910)	(1.064)	(1.203)	(1.317)	(1.411)	(1.500)
Observations	10,232	10,201	10,170	10,139	10,108	10,077	10,046	10,015	9,984	9,953
R-squared	0.920	0.852	0.778	0.705	0.637	0.577	0.527	0.490	0.463	0.440
Number of state	31	31	31	31	31	31	31	31	31	31

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	f11d.en_gr	f12d.en_gr	f13d.en_gr	f14d.en_gr	f15d.en_gr	f16d.en_gr	f17d.en_gr	f18d.en_gr	f19d.en_gr	f20d.en_gr
c.dh#c.eli (High)	-0.154***	-0.154***	-0.152***	-0.148***	-0.143***	-0.134***	-0.124**	-0.111**	-0.0976**	-0.0835*
	(0.0463)	(0.0475)	(0.0482)	(0.0486)	(0.0487)	(0.0483)	(0.0475)	(0.0464)	(0.0454)	(0.0448)
c.dl#c.eli (Low)	-0.0844	-0.0804	-0.0755	-0.0709	-0.0650	-0.0577	-0.0504	-0.0431	-0.0353	-0.0280
	(0.0614)	(0.0636)	(0.0650)	(0.0660)	(0.0667)	(0.0667)	(0.0659)	(0.0645)	(0.0630)	(0.0612)
L.en_gr	0.335***	0.306***	0.282***	0.259***	0.240***	0.227***	0.217***	0.212***	0.210***	0.209***
	(0.0388)	(0.0399)	(0.0406)	(0.0413)	(0.0416)	(0.0413)	(0.0408)	(0.0402)	(0.0396)	(0.0393)
L2.en_gr	-0.338***	-0.309***	-0.285***	-0.262***	-0.244***	-0.230***	-0.221***	-0.215***	-0.214***	-0.213***
	(0.0387)	(0.0398)	(0.0405)	(0.0412)	(0.0414)	(0.0412)	(0.0407)	(0.0400)	(0.0394)	(0.0391)
time	0.000356***	0.000380***	0.000403***	0.000424***	0.000445***	0.000463***	0.000479***	0.000493***	0.000505***	0.000515***
	(7.15e-05)	(7.46e-05)	(7.71e-05)	(7.94e-05)	(8.13e-05)	(8.27e-05)	(8.38e-05)	(8.46e-05)	(8.50e-05)	(8.56e-05)
Constant	-7.872***	-8.409***	-8.908***	-9.391***	-9.847***	-10.26***	-10.63***	-10.94***	-11.20***	-11.43***
	(1.582)	(1.650)	(1.706)	(1.757)	(1.799)	(1.831)	(1.854)	(1.872)	(1.882)	(1.894)
Observations	9,922	9,891	9,860	9,829	9,798	9,767	9,736	9,705	9,674	9,643
R-squared	0.421	0.406	0.394	0.384	0.376	0.371	0.368	0.366	0.366	0.366
Number of state	31	31	31	31	31	31	31	31	31	31

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
VARIABLES	f21d.en_gr	f22d.en_gr	f23d.en_gr	f24d.en_gr	f25d.en_gr	f26d.en_gr	f27d.en_gr	f28d.en_gr	f29d.en_gr	f30d.en_gr
c.dh#c.eli (High)	-0.0705	-0.0569	-0.0431	-0.0301	-0.0184	-0.00703	0.00313	0.0117	0.0205	0.0290
	(0.0448)	(0.0450)	(0.0455)	(0.0461)	(0.0468)	(0.0475)	(0.0484)	(0.0492)	(0.0501)	(0.0510)
c.dl#c.eli (Low)	-0.0222	-0.0161	-0.00978	-0.00529	-0.00128	0.00275	0.00670	0.00994	0.0135	0.0177
	(0.0595)	(0.0578)	(0.0561)	(0.0543)	(0.0528)	(0.0516)	(0.0507)	(0.0497)	(0.0491)	(0.0486)
L.en_gr	0.206***	0.203***	0.203***	0.202***	0.200***	0.199***	0.197***	0.190***	0.183***	0.174***
	(0.0395)	(0.0399)	(0.0405)	(0.0413)	(0.0423)	(0.0434)	(0.0445)	(0.0456)	(0.0464)	(0.0469)
L2.en_gr	-0.210***	-0.207***	-0.207***	-0.206***	-0.205***	-0.203***	-0.201***	-0.195***	-0.188***	-0.179***
	(0.0393)	(0.0398)	(0.0404)	(0.0412)	(0.0423)	(0.0434)	(0.0445)	(0.0456)	(0.0464)	(0.0469)
time	0.000525***	0.000535***	0.000543***	0.000549***	0.000555***	0.000559***	0.000565***	0.000572***	0.000580***	0.000591***
	(8.67e-05)	(8.79e-05)	(8.91e-05)	(9.04e-05)	(9.17e-05)	(9.30e-05)	(9.45e-05)	(9.62e-05)	(9.77e-05)	(9.93e-05)
Constant	-11.66***	-11.88***	-12.07***	-12.21***	-12.33***	-12.44***	-12.56***	-12.72***	-12.91***	-13.14***
	(1.917)	(1.944)	(1.971)	(1.999)	(2.028)	(2.057)	(2.089)	(2.125)	(2.159)	(2.192)
Observations	9,612	9,581	9,550	9,519	9,488	9,458	9,427	9,396	9,365	9,334
R-squared	0.367	0.368	0.370	0.372	0.374	0.376	0.378	0.380	0.382	0.384
Number of state	31	31	31	31	31	31	31	31	31	31

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1