UNIVERSITY OF WAIKATO

Hamilton
New Zealand

Government Mandated Lockdowns Do Not Reduce Covid-19 Deaths: Implications for Evaluating the Stringent New Zealand Response

John Gibson

Working Paper in Economics 6/20

June 2020

John Gibson

School of Accounting, Finance
and Economics
University of Waikato
Private Bag 3105
Hamilton
New Zealand, 3240

Tel: +64 (7) 838 4289

Email: john.gibson@waikato.ac.nz

Abstract

The New Zealand policy response to Coronavirus (Covid-19) was the most stringent in the world during the Level 4 lockdown. At least ten billion New Zealand dollars of output (≈3.3% of GDP) were lost then, compared to staying at Level 2. For lockdown to be optimal requires large health benefits to offset these output losses. Forecast deaths from epidemiological models are not valid counterfactuals, due to poor identification. Instead, I use empirical data, based on variation amongst United States counties, over one-fifth of which just had social distancing rather than lockdown. Political drivers of lockdown provide identification. Lockdowns do not reduce Covid-19 deaths. This pattern is visible on each date that key lockdown decisions were made in New Zealand. The ineffectiveness of lockdowns implies New Zealand suffered large economic costs for little benefit in terms of lives saved.

JEL Codes

C21, I18

Keywords

Covid-19
deaths
impact evaluation
lockdown
response stringency
New Zealand

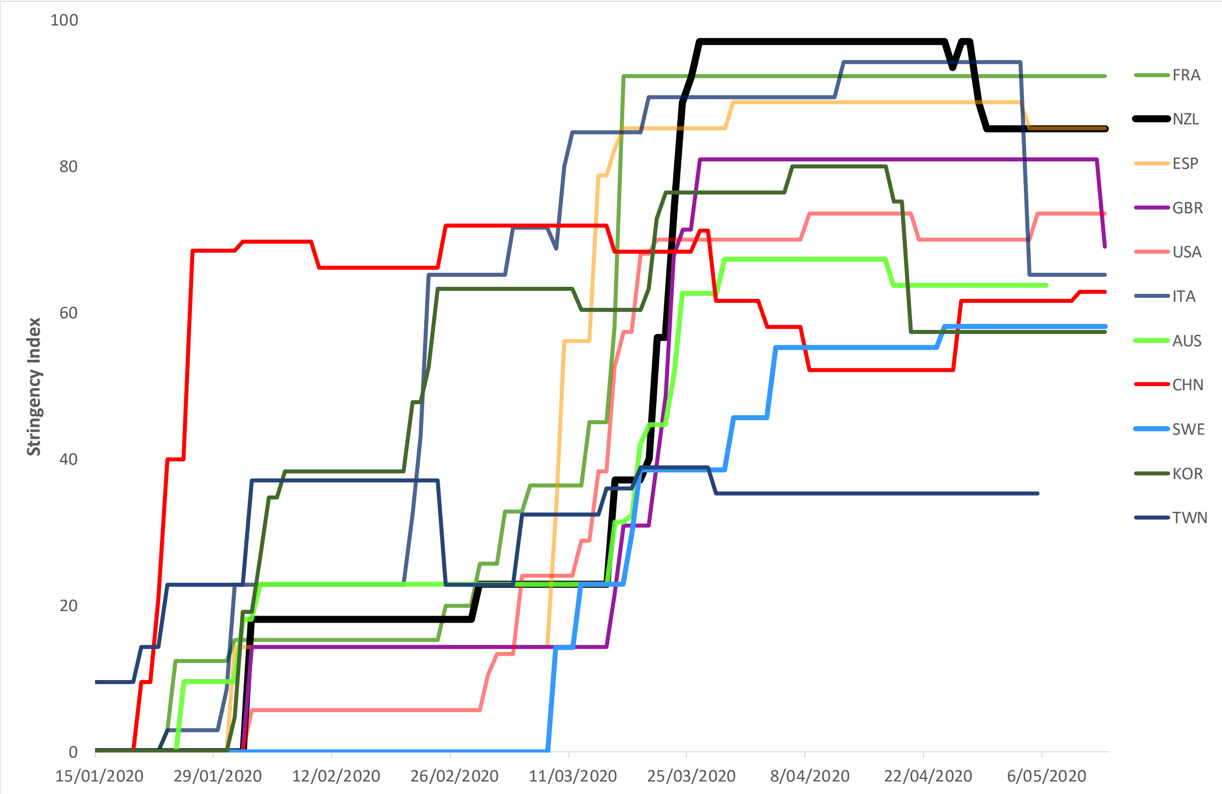
Acknowledgement

Assistance with the mapping from Geua Boe-Gibson is acknowledged.

I. Introduction

On March 23, 2020 New Zealand's Prime Minister announced a nationwide lockdown for four weeks, to start on March 25. On April 20, the lockdown was extended until April 27. The lockdown was Level 4 of the Coronavirus alert system - the 'eliminate' level. The levels had been introduced just two days earlier, starting first at Level 2 - the 'reduce' level – and jumping to Level 3 - the 'restrict' level - during the Prime Ministerial statement. With these decisions, between March 25 and April 27, New Zealand had the most stringent settings for Coronavirus in the world, based on 17 indicators of government response (Hale *et al*. 2020). Figure 1 shows that the New Zealand stringency index from March 25 exceeded that for countries like Italy, Spain and France who by then had thousands of Covid-19 deaths.

Figure 1: New Zealand
Had the Most Stringent Government Response to Coronavirus



Treasury assume that output at Level 4 was reduced by 40%, at Level 3 by 25%, and at Level 2 by 10% to15% (Treasury, 2020). Even with a V-shaped shock rather than a U or L, 33 days of Level 4 and 19 of Level 3 (that ended May 13) would reduce output by ten billion dollars (≈3.3% of GDP) compared to staying in Level 2 throughout. If there is hysteresis in unemployment, or spillover effects in business failures, then long-term economic costs of jumping to Level 4 are likely far higher. Roughly speaking, the brief time at Level 2 had restrictions slightly less stringent than what Australia maintained throughout (Figure 1).

One would assume that rigorous cost-benefit analyses accompanied the decision to set the most stringent policy response in the world. Yet Cabinet papers released six weeks later suggest not: the government ignored advice from the Ministry of Health to stay at Level 2 for 30 days, instead jumping to Level 3 after just two days, then Level 4 two days later (Daalder 2020). Two epidemiological simulations seem to have played a key role: the Imperial College forecast of 0.51 million Covid-19 deaths in the U.K. and 2.2 million in the U.S. if no changes in individual behavior or in control measures occurred (Ferguson *et al.* 2020) and forecasts by University of Otago academics with an on-line simulator (http://covidsim.eu) that ranged from seven Covid-19 deaths (assuming low infectiousness, R_0=1.5 and 50% general contact reduction for nine months) to 14,400 (highly infectious, R_0=3.5, just 25% contact reduction for six months), with a mean across the six forecasts of 8,300 deaths (Wilson *et al.* 2020).

Even although the Imperial College forecast was not for New Zealand, it seemed to shift local strategy away from 'flatten the curve' mitigation to suppression, where:

> '…you want to have a series of small peaks over a longer period of time and you amplify up quite stringent controls … then as it goes down again, you can ease those and be prepared to ramp them up again' (Director-General of Health, March 19, 2020).

This description matches a chart in the Imperial College forecast, for a suppression strategy in place for two years (Daalder 2020). The highest death forecasts from the University of Otago may have influenced comments made by the Prime Minister in announcing the lockdown:[1]

> 'If community transmission takes off … our health system will be inundated, and tens of thousands New Zealanders will die … it is the reality we have seen overseas… We can stop the spread by staying at home and reducing contact… That is why … effective immediately we will move to Alert Level 3 … after 48 hours we will move to Level 4.'

It is unfortunate that epidemiological simulations had such an impact, as they use flawed models. The Susceptible, Infected, Recovered (SIR) model, and variants with Exposed and Dead (SEIRD), have infectious people mixing (homogeneously) with others; each person has equal chances to meet any other, regardless of the health status of the two persons. Yet in reality, people engage in preventative behaviour to reduce risk of exposure. Allow for this situation and some public actions designed to reduce disease spread may do more harm (Toxvaerd, 2019). These models also have too many degrees of freedom, so are poorly identified from short-run data on cases. For example, Korolev (2020) shows long-run forecasts of U.S. COVID-19 deaths from observationally equivalent SEIRD models range from about 30,000 to over a million. Forecast deaths depend on arbitrary choices by researchers, and data available at the time cannot show which forecast is right as so many models are observationally equivalent in the short-run.

In another case, Swedish researchers using the Imperial College approach forecast (in mid-April) 80,000 Covid-19 deaths by mid-May (Gardner *et al.* 2020). In fact, just 3500 died

---

[1] https://www.rnz.co.nz/news/political/412403/all-of-new-zealand-must-prepare-to-go-in-self-isolation-now-prime-minister

by May 15, with the forecast more than 20-times too high.[2] A final example is the University of Otago forecasts, which had assumed no case tracing and isolation. Using the same simulation model, Harrison (2020) set tracing and isolation success at 50 percent and forecast deaths fell by 96 percent.

Rather than using poorly identified simulation models, I use data on Covid-19 deaths, as of each date key lockdown decisions were made in New Zealand. Deaths data are more reliable than cases data (Homburg, 2020). My research design exploits variation among U.S. counties, over one-fifth of which just had social distancing rather than lockdown. Political drivers of lockdown provide identification. If the Prime Ministerial claim, that without lockdown tens of thousands of New Zealanders would die, is correct then one would expect to see more deaths in places without a lockdown. This may explain global fascination with Sweden, as a country without lockdown. However, a within-country research design has two benefits: less variation in measuring Covid-19 deaths than in between-country comparisons and it better suits the highly clustered nature of Covid-19. For example, Lombardy's Covid-19 death rate was 1500 per million versus 300 per million elsewhere in Italy. The New York death rate (by May 15) was 1410 per million but just 190 per million in the other 49 states. Taking China's data at face value, Hubei's death rate was 76 per million versus 0.12 per million elsewhere. With such clustering, analyses relying on national averages may mislead.[3]

Whether a county had a lockdown has no effect on Covid-19 deaths; a non-effect that persists over time. Cross-country studies also find lockdowns are superfluous and ineffective (Homberg 2020). This ineffectiveness may have several causes. Real-time activity indicators suggest the threat of Covid-19, rather than lockdown itself, drives behaviour (Chetty *et al*. 2020). There may also be offsetting Peltzman effects, where risky behaviour is more likely if safety measures are mandated. Theory shows public health interventions can paradoxically increase infection rates due to these risk-compensation effects (Toxvaerd 2019, Dasaratha 2020). Notably, lockdown is not historically used to deal with epidemics, which is why some epidemiologists (for example, Giesecke 2020) remain opposed. A review, prompted by the 2006 U.S. Pandemic Influenza Plan, argued against confining large groups, such as an entire city:

> 'There are no historical observations or scientific studies that support the confinement by quarantine of groups of possibly infected people for extended periods in order to slow the spread of influenza….The negative consequences of large-scale quarantine are so extreme…that this mitigation measure should be eliminated from serious consideration' (Inglesby *et al.* 2006, p.371).

[2] Sweden is informative because their strategy did not change. Elsewhere, defenders of the epidemiological models can rationalize the overstated predictions as resulting from governments adopting more stringent responses to Coronavirus than the models had assumed. In this regard, one is reminded of the comment of Sir Karl Popper about unscientific theories that seemed 'to be able to explain practically everything that happened within the fields to which they referred. … Whatever happened always confirmed it.' (Popper 1962, pp.34-35).

[3] Even U.S. state-level data may mislead, as 75 percent of total variance in death rates is within rather than between states.

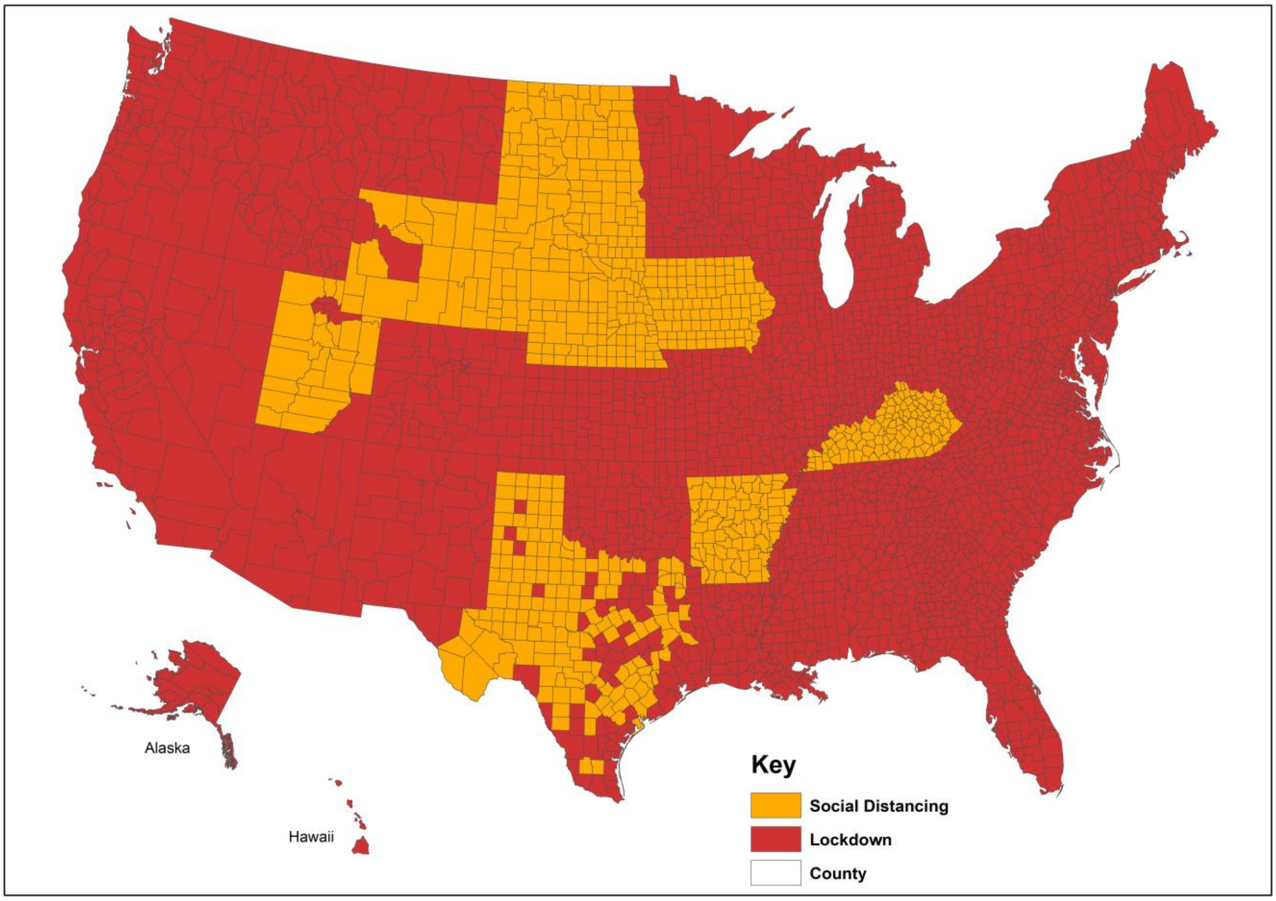
Instead, isolation of infected individuals was historically relied upon - and eventual use of this in Wuhan, rather than lockdown, was key to breaking the disease spread (Stone 2020).

2. County-level Evidence from the United States

The U.S. provides useful variation for estimating the impact of lockdowns because the Tenth Amendment to the Constitution gives police powers to states, which limits the federal response to epidemics (Inglesby *et al.* 2006). The first-shelter-in-place or stay-at-home orders were issued on 14 March for San Francisco-area counties, and were followed by a California-wide lockdown from March 19. Many other governors quickly issued state-wide lockdowns, but in others (for example, Texas), weaker 'state of disaster' notices let cities and counties adopt local lockdown rules, albeit with federal social distancing guidelines in the background.

The varied situation that resulted is seen in Figure 2, which shows counties subject to lockdown orders (technically, government-ordered community quarantine) and those with just social distancing. Data are from American Red Cross reporting on emergency regulations for each county, from March 14 onward. The map was first posted by ESRI (of ArcGIS fame) on April 3, updating through md-April if rules for a county changed.

Figure 2: County-level Variation in Lockdown Orders
as at Early April, 2020



With such a dynamic situation, care must be taken in defining the treatment variable. One approach is to look at the timing and duration of lockdown orders. Yet many lockdowns are still in place, as of mid-May, so a duration treatment variable cannot be defined and could not have provided evidence at the time of key decisions in New Zealand. Instead, I use the binary treatment of being subject to lockdown as of early April; the situation seen in Figure 2. All data sources (details in Appendix A, summary statistics in Appendix B) were available to inform New Zealand policy makers from mid-March (the map data were available from the Red Cross, ESRI later made them more conveniently available).

The number of Covid-19 deaths in a county is highly skewed, with standard deviation over eight times the mean (for deaths to May 11). Therefore, the log of the number of deaths is the outcome variable for the regressions, reducing the coefficient of variation (CoV) to 1.3.[4] Death rates could be used (CoV=2.5), but are less flexible than log deaths with log population as a covariate (rates force the coefficient on log population to 1.0). To get percentage impacts of lockdown from the log outcome, I use $100 \times \left(e^{\hat{\beta}-0.5\hat{V}(\hat{\beta})} - 1\right)$ with confidence intervals from the approximate unbiased variance estimator of van Garderen and Shah (2002).

The regressions use 22 control variables, including county population and density, the elder share, the share in nursing homes, nine other demographic and economic characteristics and a set of regional fixed effects.[5] These controls explain about two-thirds of variation in log deaths (as of mid-May). Even with these controls, the errors for the log death equations may correlate with treatment status, if selection into the treatment group (77 percent of counties) is due to unobservables. Political drivers of lockdown are plausible instruments; counties without lockdown are all in states with Republican governors and if a gubernatorial election is set for November 2020 (11 are) lockdown seems more likely. Conditional on the state-level factors, the extent a county became more partisan between the 2012 and 2016 Presidential elections, relative to the state-level change, affects odds of a lockdown. It is hard to think of other paths for these variables to affect Covid-19 deaths than via political calculations about lockdown. I use a control function version of IV, with first stage residuals added to OLS outcome equations, because the percentage impact estimator (and its variance) is based on OLS.

The last factor affecting estimator choice is the prospect of spatial autocorrelation. Neighbours of a county with unexplainably more deaths themselves likely have more deaths, given the epidemic spread of Covid-19. I cluster at the state level, to allow for correlations in the errors for counties in the same state. Clustered errors can be conservative, in not letting intra-cluster correlations vary and in not allowing between-cluster correlations (Gibson *et al.* 2014). As a variant I also use a spatially autoregressive model with autoregressive errors,

[4] Many counties have zero deaths so the inverse-hyperbolic-sine transformation is used. This is identical to using logarithms for non-zero observations, but lets zeros be used without resorting to crude adjustments like adding one to all values before logging (Gibson *et al.* 2017).

[5] Using the Standard Federal Administrative Regions (SFARs). With some of the instrumental variables defined at the state level, using state fixed effects introduces a collinearity problem.

estimated by generalized spatial two-stage least squares (Drukker *et al.* 2013). This lets errors correlate with errors of neighbouring counties (and neighbours of neighbours), and allows for spatial spillovers in deaths. The results in Appendix C show these spillovers are present.

The main regression results are in Table 1. The first column has the first-stage results, for which counties have lockdown. The F-test for excluding the instruments is 4.1 (p<0.02) if using clustered standard errors, or 46 (p<0.01) if using the spatial error model. The remaining columns have OLS and IV results for cumulative deaths at three dates matching key decisions made in New Zealand: March 23 when Level 3 was announced with the two-day warning for Level 4; April 20 when Level 4 was extended; and, May 11 when a staged move to Level 2 over ten days was announced. The aim in showing results for these dates is to see how any evidence for whether lockdowns reduce Covid-19 deaths evolved; data used here were available at the time of these decisions so it is not a question of being wise in hindsight.

There is no evidence that counties with a lockdown have fewer deaths. In the OLS results and the IV control function results for all three dates, the coefficient on lockdown is statistically insignificant.[6] The same evidence of lockdowns having no impact also shows up in the spatially autoregressive models in Appendix C. Given the strength of the instruments (for example, an F-test of 46 for excluding them, using the spatial error model), an insignificant effect of lockdown is unlikely due to weak instruments. A test of over-identifying restrictions also reveals no concerns (p<0.18)

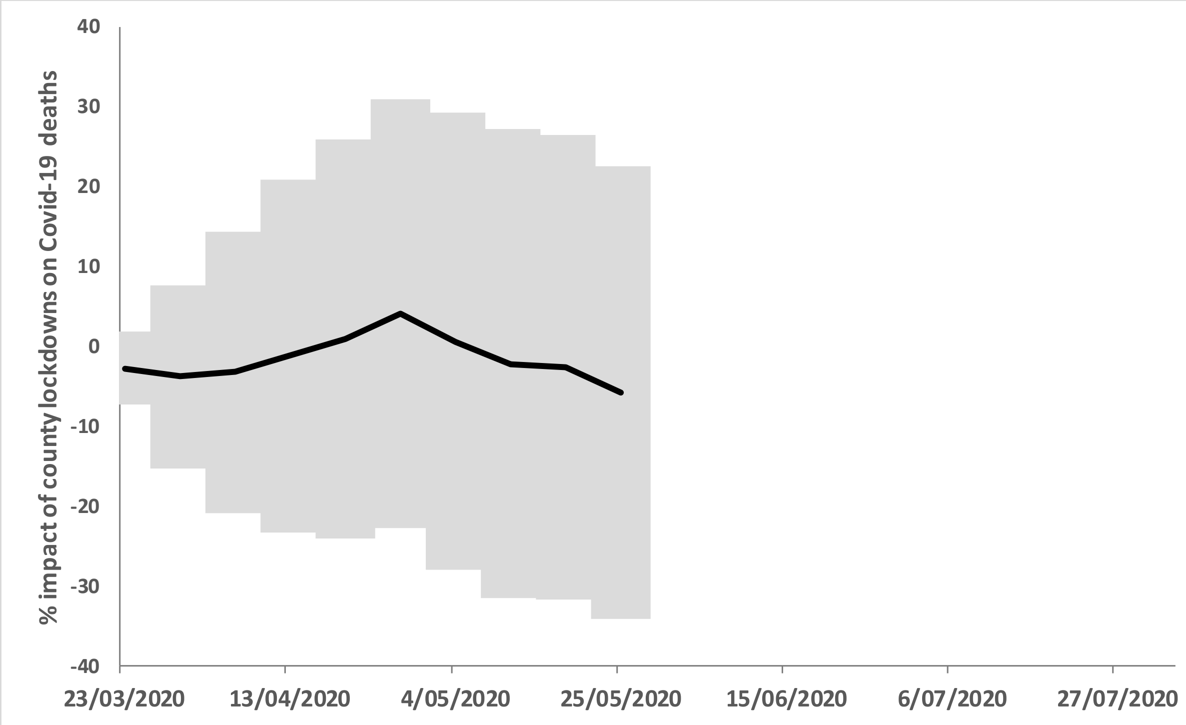
It typically takes three weeks for a SARS-CoV-2 infection to cause Covid-19 death (Homburg, 2020) so one may expect a future rise in deaths in counties with no lockdown. To monitor this, Figure 3 shows percentage impacts (and 95% confidence intervals) of lockdowns on Covid-19 deaths, from models estimated on the data every Monday from March 23. The corresponding charts derived from spatially autoregressive models are in Appendix C. On just one of 40 test occasions (ten Mondays, from 23 March to 25 May, over four models) does the 95% confidence interval not include zero (May 25, using the spatial control function approach). However, once an adjustment is made for multiple hypothesis testing, using a bonferroni correction, it requires statistical significance at the α/n level, which is .00125. This is 25-times smaller than the actual p-value. So the firmest conclusion is, that over the ten weeks since New Zealand's March 23 lockdown decision, there is no evidence of more Covid-19 deaths in places that had no lockdown.

[6] The statistical insignificance of the coefficient on the first-stage residuals implies (via the added-variable form of the Hausman test) that potential selection on unobservables (of which counties have lockdown) may not be a cause of significant bias in OLS results.

Figure 3: Evolving Estimates of the Impact of County Lockdowns on Covid-19 Deaths

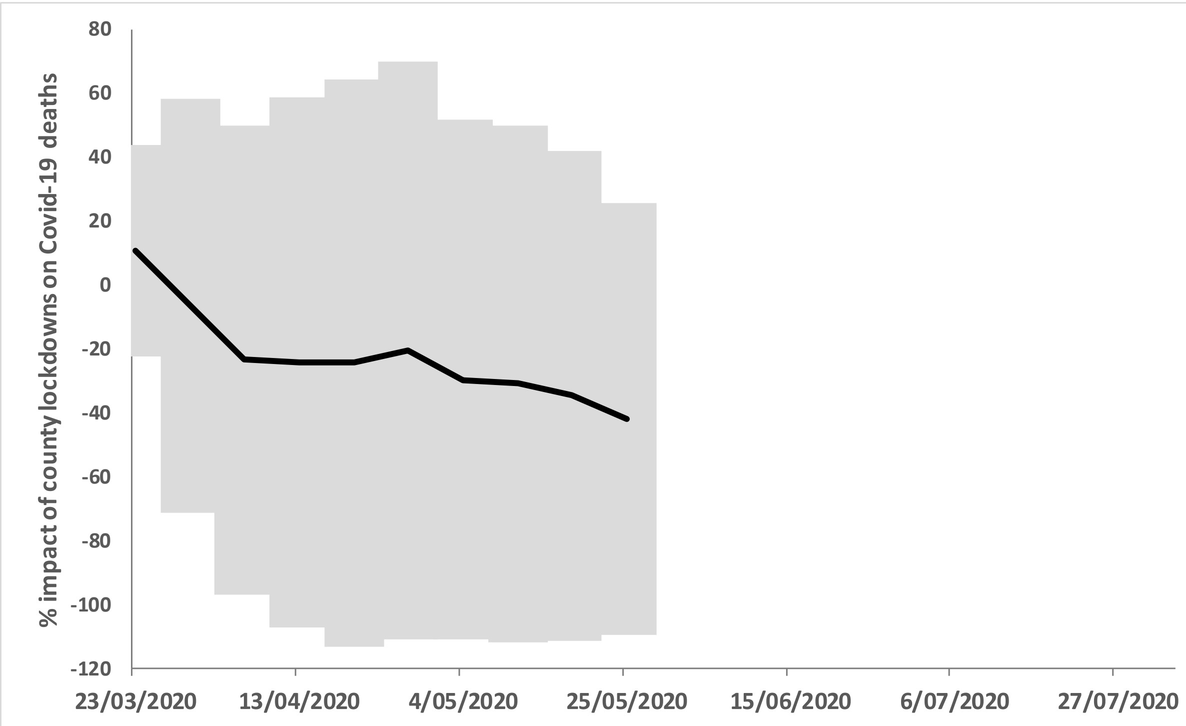
(a) OLS Model

Assuming Selection into Lockdown is on Observables



(b) Control Function Model

Allowing Selection on Unobservables



Notes

Shaded regions show 95% confidence intervals. Models use standard errors clustered at State level.

The insignificance of lockdown variables is not due to failure of the models to explain the cross-county pattern of deaths; almost two-thirds of variation is explained for cumulative deaths by early May. For example, the models show deaths are higher if the elderly or those in nursing homes are a higher share of the population; patterns noted in popular discussion of Covid-19. Deaths are higher if whites are a lower share of the population and blacks a higher share, as noted elsewhere (Millett *et al.* 2020). Counties with higher earnings, more inequality and more people without health insurance experience more deaths. It may seem odd that fewer deaths occur if the smoking rate is higher but the OpenSAFELY study of 17 million NHS patients in the United Kingdom (Williamson *et al.* 2020) finds similar; current smokers are less likely than others to die (as hospital in-patients) with confirmed COVID-19.

Five sensitivity analyses confirm the result that lockdowns are ineffective at reducing Covid-19 deaths. The first weights by county population; the 5th percentile county has under 3000 people while the 95th percentile has 450,000 so a case can be made for more weight on populous counties. The second uses death rates (by May 11). The third uses IV-Poisson count data models, and the fourth uses LIML which may be preferred if there are weak instruments. In all four of these alternative approaches, lockdowns have no impact on Covid-19 deaths. The last sensitivity analysis is just for Texas, which had a more even split of 89 counties with lockdown and 165 with social distancing. The IV results show no effect of lockdown but with OLS it seems that counties with a lockdown have more deaths – a pattern strengthening over time (e.g. lockdown counties have 37.1% (SE=18.6%) more deaths by May 11).[7]

3. Summary and Implications for New Zealand

Lockdowns are ineffective at reducing Covid-19 deaths. Variation amongst counties in the United States, where over one-fifth had no lockdown, shows no impact from lockdowns. Specifically, one cannot reject the hypothesis of zero difference in deaths between lockdown and non-lockdown counties, even after three months. Thus, there is no evidence to suggest that lockdowns saved lives. Using these results to inform a counterfactual of what would have happened if New Zealand had not gone into a Level 4 lockdown faces the criticism that the setting is different. Yet it is a universal force of human nature - privately taking steps to reduce exposure to a new risk - that likely makes lockdown ineffective compared to just practicing good hygiene and social distancing.

A non-economist might say ‘what difference does it make?’ If people would reduce interactions anyway, due to perceived Covid-19 risks, having government force them to stay home would seem costless. Yet as economists know, a government *diktat* approach runs into

[7] Only seven percent of Texas counties with (or soon to) lockdown had a Covid-19 death by March 23 (six percent nationally) so it was not deaths driving lockdown. Two months later, by May 18, the risk a county had any Covid-19 deaths, conditional on having no deaths by March 23, had increased by significantly more for lockdown counties compared to those that did not lockdown, which further points to the ineffectiveness of lockdowns.

the central planning problem, namely, that no central planner has all the information (collectively) held by parties involved in voluntary exchange (Hayek 1945). For example, absent lockdown, if a butcher felt they could operate safely and if customers felt they could safely shop at this butchery, voluntary and beneficial exchange could have occurred. Instead, under the central planning approach applied in New Zealand, butchers were shut but supermarkets selling meat were not. Potentially, much economic surplus (for both consumers and producers) was lost.

In terms of implications for the future, these results add to the cross-country evidence that lockdowns were ineffective (Homberg 2020, Stone 2020). This was also the prior view in public health. Inglesby *et al* (2006, p.371), for example, noted that 'It is difficult to identify circumstances in the past half-century when large-scale quarantine has been effectively used in the control of any disease.' So, when the next pandemic occurs, the Covid-19 lockdowns should not be considered a success that should be replicated, no matter how strong an attempt by media and others to present that narrative. In terms of the (recent) past, the ineffectiveness of lockdowns implies that New Zealand suffered large output losses, of ten billion dollars or more, for no likely benefit in terms of lives saved as a result of the decision to move almost immediately from Level 2 to Level 4. Notably, this decision went against Ministry of Health advice to stay at Level 2 for 30 days. If decision-making from March and April is reviewed, any claim that lockdown was necessary to save lives can be treated with strong scepticism. It is especially concerning that there were data available, on the dates of those key decisions, that show that lockdowns are ineffective at reducing Covid-19 deaths.

References

Chetty, R., Friedman, J.N., Hendren, N. and Stepner, M., 2020. Real-Time Economics: A New Platform to Track the Impacts of COVID-19 on People, Businesses, and Communities Using Private Sector Data. https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf

Daalder, M. 2020. Long read: The month that changed New Zealand. https://www.newsroom.co.nz/2020/05/13/1168837/long-read-the-month-that-changed-new-zealand

Dasaratha, K. 2020. Virus dynamics with behavioural responses. *mimeo* arXiv:2004.14533

Drukker, D., Prucha, I. and Raciborski, R., 2013. Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. *Stata Journal*, *13*(2), pp.221-241.

Ferguson N., Laydon D. and 29 others. 2020. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. *Mimeo* Imperial College.

Gardner, J., Willem, L., van der Wijngaart, W., Kamerlin, S., Brusselaers, N. and Kasson, P., 2020. Intervention strategies against COVID-19 and their estimated impact on Swedish healthcare capacity. *medRxiv*. http://doi.org/10.1101/2020.04.11.20062133

Gibson, J., Datt, G., Murgai, R. and Ravallion, M., 2017. For India's rural poor, growing towns matter more than growing cities. *World Development*, *98*(1), pp.413-429.

Gibson, J., Kim, B. and Olivia, S., 2014. Cluster-corrected standard errors with exact locations known: an example from rural Indonesia. *Economics Bulletin*, *34*(3), pp.1857-1863.

Giesecke, J. 2020. The invisible pandemic. *The Lancet* 6736(20), 31035-7.

Hale, T., Webster, S., Petherick, A., Phillips, T. and Kira B. 2020. *Oxford COVID-19 Government Response Tracker*, Blavatnik School of Government.

Harrison, I., 2020. The Ministry of Health's modelling of the impact of the Coronavirus on New Zealand: A look behind the headlines. *mimeo* Tailrisk Economics, Wellington. http://www.tailrisk.co.nz/documents/Corona.pdf

Hayek, F.A., 1945. The use of knowledge in society. *American Economic Review*, *35*(4), pp.519-530.

Homburg, S., 2020. Effectiveness of Corona Lockdowns: Evidence for a Number of Countries. *Hannover Economic Papers* No.dp-671. Leibniz Universität Hannover, Wirtschaft-swissenschaftliche Fakultät.

Inglesby, T., Nuzzo, J.B, O'Toole, T. and Henderson, D.A., 2006. Disease mitigation measures in the control of pandemic influenza. *Biosecurity and Bioterrorism: Biodefense Strategy, Practice, and Science*, *4*(4), pp.366-375.

Korolev, I., 2020. Identification and Estimation of the SEIRD Epidemic Model for COVID-19. (April 20, 2020). Available at: http://dx.doi.org/10.2139/ssrn.3569367

Millett, G., Jones, A. and 10 others. 2020. Assessing differential impacts of COVID-19 on Black communities. *medRxiv*. https://doi.org/10.1101/2020.05.04.20090274

Popper, K. 1962. *Conjectures and Refutations: The Growth of Scientific Knowledge*. Basic Books, New York, 1962.

Stone, L. 2020. Lockdowns don't work. *Public Discourse* (April 21, 2020) https://www.thepublicdiscourse.com/2020/04/62572/

Toxvaerd, F., 2019. Rational disinhibition and externalities in prevention. *International Economic Review*, *60*(4), pp.1737-1755.

Treasury. 2020. *Treasury Report T2020/973: Economic scenarios* - 13 April 2020. https://treasury.govt.nz/publications/tr/treasury-report-t2020-973-economic-scenarios-13-april-2020

Van Garderen, K. and Shah, C., 2002. Exact interpretation of dummy variables in semilogarithmic equations. *The Econometrics Journal*, *5*(1), pp.149-159.

Williamson, E., Walker, A. and 28 others. 2020. OpenSAFELY: factors associated with COVID-19-related hospital death in the linked electronic health records of 17 million adult NHS patients. *medRxiv*. https://doi.org/10.1101/2020.05.06.20092999

Wilson, N., Barnard, L., Kvalsvig, A. and Baker, M., 2020. Potential Health Impacts from the COVID-19 Pandemic for New Zealand if Eradication Fails: Report to the NZ Ministry of Health.

Table 1: County-level Impacts of Lockdowns on Covid-19 Deaths

	First stage model (Lockdown=1)	ln (deaths, by March 23) OLS	ln (deaths, by March 23) IV/CF	ln (deaths, by April 20) OLS	ln (deaths, by April 20) IV/CF	ln (deaths, by May 11) OLS	ln (deaths, by May 11) IV/CF
Lockdown (=1, otherwise social distancing)		-0.028	0.112	0.017	-0.062	-0.007	-0.154
		(0.024)	(0.154)	(0.127)	(0.667)	(0.155)	(0.665)
Residuals (from first stage for lockdown)			-0.150		0.085		0.159
			(0.163)		(0.675)		(0.658)
ln (county population, 2009)	0.078**	0.035	0.024	0.506***	0.512***	0.666***	0.678***
	(0.037)	(0.024)	(0.026)	(0.067)	(0.089)	(0.070)	(0.091)
ln (county population density)	-0.015	0.048*	0.051*	0.120	0.119	0.112	0.109
	(0.029)	(0.027)	(0.027)	(0.072)	(0.076)	(0.073)	(0.078)
Share of county age 75 years or older	-1.241	1.924***	2.054***	6.415***	6.341***	6.908***	6.771***
	(1.229)	(0.666)	(0.718)	(1.965)	(1.986)	(2.011)	(1.939)
Share of county population in nursing homes	-1.616*	0.854**	1.151**	3.352**	3.184	4.369**	4.055
	(0.944)	(0.373)	(0.498)	(1.597)	(2.053)	(1.921)	(2.420)
Male share of county population	0.265	0.878***	0.836***	3.262***	3.286***	3.187***	3.231***
	(0.414)	(0.268)	(0.264)	(0.963)	(1.014)	(1.030)	(1.083)
White share of county population	-0.087	-0.337**	-0.325**	-1.119**	-1.126**	-1.524***	-1.536***
	(0.373)	(0.159)	(0.155)	(0.423)	(0.432)	(0.457)	(0.477)
Black share of county population	0.585	-0.110	-0.181	0.750	0.790	1.243*	1.318**
	(0.389)	(0.160)	(0.181)	(0.663)	(0.648)	(0.719)	(0.638)
ln (median income for county, 2010 census)	0.059	0.328***	0.319***	1.574***	1.579***	1.691***	1.701***
	(0.111)	(0.111)	(0.109)	(0.291)	(0.297)	(0.315)	(0.323)
Gini coefficient	0.166	0.668***	0.657***	3.215***	3.221***	3.022***	3.033***
	(0.381)	(0.179)	(0.179)	(0.625)	(0.617)	(0.576)	(0.567)
Unemployment rate	-0.154	-0.210	-0.306	-2.011	-1.956	-2.548	-2.446
	(1.139)	(0.307)	(0.301)	(1.465)	(1.576)	(1.645)	(1.781)
Share of housing units with rental occupier	-0.691***	0.392	0.489	0.362	0.307	0.245	0.143
	(0.239)	(0.273)	(0.309)	(0.905)	(0.891)	(1.012)	(0.938)
Share of population without health insurance	2.359**	1.072***	0.746	3.976***	4.160*	4.697***	5.041**
	(1.064)	(0.398)	(0.526)	(1.427)	(2.303)	(1.626)	(2.451)

Continued

Table 1 *continued*

	First stage model (Lockdown=1)	ln (deaths, by March 23) OLS	IV/CF	ln (deaths, by April 20) OLS	IV/CF	ln (deaths, by May 11) OLS	IV/CF
Adult smoking rate	-0.205	-0.207*	-0.206*	-1.248**	-1.248**	-1.380**	-1.380**
	(0.559)	(0.107)	(0.106)	(0.526)	(0.527)	(0.586)	(0.587)
Gubernatorial election set for 2020	0.147						
	(0.094)						
Governor is Democratic	0.170						
	(0.127)						
Change in county partisanship, 2012-16	0.358*						
	(0.216)						
Constant	-0.633	-4.514***	-4.427***	-23.164***	-23.213***	-25.044***	-25.136***
	(1.310)	(1.233)	(1.216)	(3.201)	(3.261)	(3.439)	(3.510)
R-squared	0.430	0.238	0.240	0.600	0.600	0.639	0.639

Notes

Models also include nine fixed effects for US regions.

Robust standard errors in ( ) clustered at state level,

***, **, * denote statistical significance at 1%, 5% and 10% levels.

N=3109 US counties.

Appendix A

Data Sources

County-level daily data on cumulative deaths related to Covid-19 are obtained from the aggregation site: https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/ who source the raw data from the Centers for Disease Control and Prevention (CDC), and from state- and local-level public health agencies. The data file starts from 22 January 2020 and updates daily. The Wayback Machine digital archive indicates that the website aggregating the data has been available at least since March 17, 2020. In a few cases, deaths are attributed to a state but not to a county (for example, from the Grand Princess cruise ship). Where local agencies changed their methodology in reporting deaths due to COVID-19 the county-level counts are retroactively adjusted, so the most recent data file should always be used.

Data on which counties have Government Ordered Community Quarantine (*aka* 'Lockdown') and which have Government Directed Social Distancing are from the Disaster Response Program of ESRI (the supplier of ArcGIS and related software and data): https://coronavirus-disasterresponse.hub.arcgis.com/app/ebe29d4c1fca4ac292d00dbd54ed37e9. The data in the map are compiled and periodically updated by the American Red Cross based on documents made publicly available by State, Tribal, Territorial and municipal governments. The data have been compiled by the Red Cross since at least March 14, 2020.

The politics data used as the instrumental variables come from two sources. The county level variable that measures changes in the Republican-Democratic gap in the vote share from the 2012 to the 2016 Presidential elections comes from the MIT Election Data and Science Lab 'County Presidential Election Returns 2000-2016' https://doi.org/10.7910/DVN/VOQCHQ. The data on States having gubernatorial elections in 2020 is from the National Governors Association at https://www.nga.org/governors/elections/ and the data on the party affiliation of the incumbent governor for each State is from https://www.nga.org/governors/

The control variables come from four sources. The estimated population of each county in 2019 is from the same source as the number of Covid-19 deaths (https://usafacts.org) in order to use a population denominator as close in time to the deaths as possible. The population density and demographic ratios (shares of population who are: age 75 or older; white; black; male; and, renters) are originally from the 2010 census, reported at the ArcGIS Hub for USA Counties (http://hub.arcgis.com/datasets/48f9af87daa241c4b267c5931ad3b226_0). The ratios use the 2010 population counts as the denominator, rather than the 2019 population estimates reported at usafacts.org in order to be internally consistent.

The median earnings, the Gini coefficient, the unemployment rate, the share uninsured and the smoking rate are from the MIT Election Data and Science Lab, whose URL is given above. These variables are also originally from the 2010 Census. Data on rest homes are from the Skilled Nursing Facilities Quality Reporting Program, covering all Medicare and Medicaid-certified nursing homes, available at:
https://www.medicare.gov/nursinghomecompare/search.html.

For each of the n=15,436 nursing homes, the certified number of beds and the total number of residents is reported, along with the facility address (including ZIP code). A few lacking resident counts get given an imputed value based on the number of beds. The estimated count of residents is aggregated to ZIP code level and then to county level using the ZIP code to FIPS crosswalk provided at: https://www.huduser.gov/portal/datasets/usps_crosswalk.html. The number of nursing home residents is expressed as a ratio to the 2019 estimate of the county population.

Appendix B

Table B1: Summary Statistics

	Mean	Std Dev	Min	Max
Deaths (as of May 11)	25.148	205.144	0.000	6024.000
Death rate, deaths per million (as of May 11)	89.327	223.659	0.000	3098.259
Lockdown (=1, otherwise social distancing)	0.770	0.421	0.000	1.000
ln (county population, 2009)	10.288	1.490	5.130	16.122
ln (county population density)	3.815	1.730	-2.110	11.199
Share of county age 75 years or older	0.072	0.024	0.013	0.203
Share of county population in nursing homes	0.011	0.012	0.000	0.233
Male share of county population	0.488	0.035	0.238	0.744
White share of county population	0.812	0.166	0.095	0.992
Black share of county population	0.088	0.147	0.000	0.879
ln (median income for county, 2010 census)	10.126	0.193	8.576	10.945
Gini coefficient	0.432	0.036	0.207	0.645
Unemployment rate	0.077	0.028	0.008	0.283
Share of housing units with rental occupier	0.233	0.075	0.042	0.763
Share of population without health insurance	0.179	0.054	0.031	0.389
Adult smoking rate	0.212	0.059	0.031	0.511
Gubernatorial election set for 2020	0.182	0.386	0.000	1.000
Governor is Democratic	0.436	0.496	0.000	1.000
Relative change in county partisanship 2012-16	0.000	0.077	-0.413	0.466

Note

Based on *N*=3109 U.S. counties.

Appendix C

Table C1: Sensitivity Analyses Using Spatial Autoregressive Models with Spatial Errors

County-level Impacts of Lockdowns on Covid-19 Deaths

Total of the Direct and Indirect Impacts Allowing for Spillovers

	First stage model (Lockdown=1)	ln (deaths, by March 23)		ln (deaths, by April 20)		ln (deaths, by May 11)	
		SPREG	IV/CF	SPREG	IV/CF	SPREG	IV/CF
Lockdown (=1, otherwise social distancing)		-0.034	-0.001	0.095	0.224	0.088	-0.167
		(0.022)	(0.104)	(0.102)	(0.471)	(0.110)	(0.504)
Residuals (from first stage for lockdown)			-0.037		-0.136		0.268
			(0.108)		(0.483)		(0.517)
ln (county population, 2009)	0.025***	0.047***	0.048***	0.774***	0.774***	0.923***	0.931***
	(0.007)	(0.014)	(0.015)	(0.065)	(0.066)	(0.066)	(0.068)
ln (county population density)	0.000	0.048***	0.050***	0.163***	0.163***	0.178***	0.180***
	(0.007)	(0.013)	(0.014)	(0.047)	(0.048)	(0.051)	(0.051)
Share of county age 75 years or older	-0.610**	1.973***	2.095***	12.743***	12.875***	12.358***	12.274***
	(0.238)	(0.495)	(0.536)	(1.866)	(1.895)	(1.878)	(1.898)
Share of county population in nursing homes	-0.063	1.488**	1.571**	5.380**	5.423**	5.871***	5.833**
	(0.303)	(0.660)	(0.700)	(2.141)	(2.154)	(2.271)	(2.281)
Male share of county population	-0.011	0.997***	1.052***	3.638***	3.661***	3.308***	3.309***
	(0.132)	(0.295)	(0.315)	(0.938)	(0.943)	(0.983)	(0.987)
White share of county population	0.001	-0.344***	-0.363***	-2.138***	-2.148***	-2.285***	-2.294***
	(0.056)	(0.109)	(0.116)	(0.406)	(0.408)	(0.423)	(0.424)
Black share of county population	0.109	-0.102	-0.110	0.783*	0.774*	1.154**	1.171**
	(0.069)	(0.105)	(0.112)	(0.440)	(0.442)	(0.470)	(0.472)
ln (median income for county, 2010 census)	0.010	0.377***	0.392***	1.602***	1.608***	1.535***	1.542***
	(0.028)	(0.069)	(0.074)	(0.210)	(0.211)	(0.214)	(0.214)
Gini coefficient	0.146	0.854***	0.893***	3.324***	3.331***	3.130***	3.177***
	(0.122)	(0.273)	(0.290)	(0.872)	(0.878)	(0.912)	(0.918)
Unemployment rate	0.187	-0.327	-0.381	-5.702***	-5.782***	-5.663***	-5.597***
	(0.221)	(0.404)	(0.435)	(1.530)	(1.548)	(1.598)	(1.612)
Share of housing units with rental occupier	-0.161**	0.413***	0.442***	0.609	0.638	0.432	0.395
	(0.076)	(0.157)	(0.168)	(0.514)	(0.523)	(0.546)	(0.553)

Table C1 *continued*

	First stage model (Lockdown=1)	ln (deaths, by March 23) SPREG	IV/CF	ln (deaths, by April 20) SPREG	IV/CF	ln (deaths, by May 11) SPREG	IV/CF
Share of population without health insurance	0.681***	1.326***	1.359***	4.214***	4.142***	5.624***	5.834***
	(0.138)	(0.276)	(0.302)	(0.932)	(0.993)	(1.005)	(1.075)
Adult smoking rate	0.037	-0.120	-0.133	-1.825***	-1.843***	-1.446***	-1.429***
	(0.075)	(0.139)	(0.148)	(0.509)	(0.513)	(0.532)	(0.535)
Gubernatorial election set for 2020	0.181***						
	(0.019)						
Governor is Democratic	0.111***						
	(0.016)						
Change in county partisanship, 2012-16	0.045						
	(0.063)						
Spatial lag of the error term	0.053***	0.025***	0.023***	0.033***	0.033***	0.034***	0.033***
	(0.001)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
Spatial lag of the dependent variable		0.014***	0.016***	0.020***	0.020***	0.017***	0.017***
		(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Pseudo *R*-squared	0.343	0.232	0.230	0.575	0.575	0.623	0.623

Notes

Models also include nine fixed effects for US regions and an intercept.

In the first column and in the spatial lag rows, cell values are coefficient estimates, otherwise they are the average total impacts, taking into account direct and indirect impacts from spillovers operating through the spatially lagged dependent variable.

For those cells, the standard errors in ( ) are calculated from delta method, otherwise they are from a heteroscedasticity-robust GMM variance estimator.

Estimation uses generalized spatial two-stage least squares, with a second-order contiguity weighting matrix.

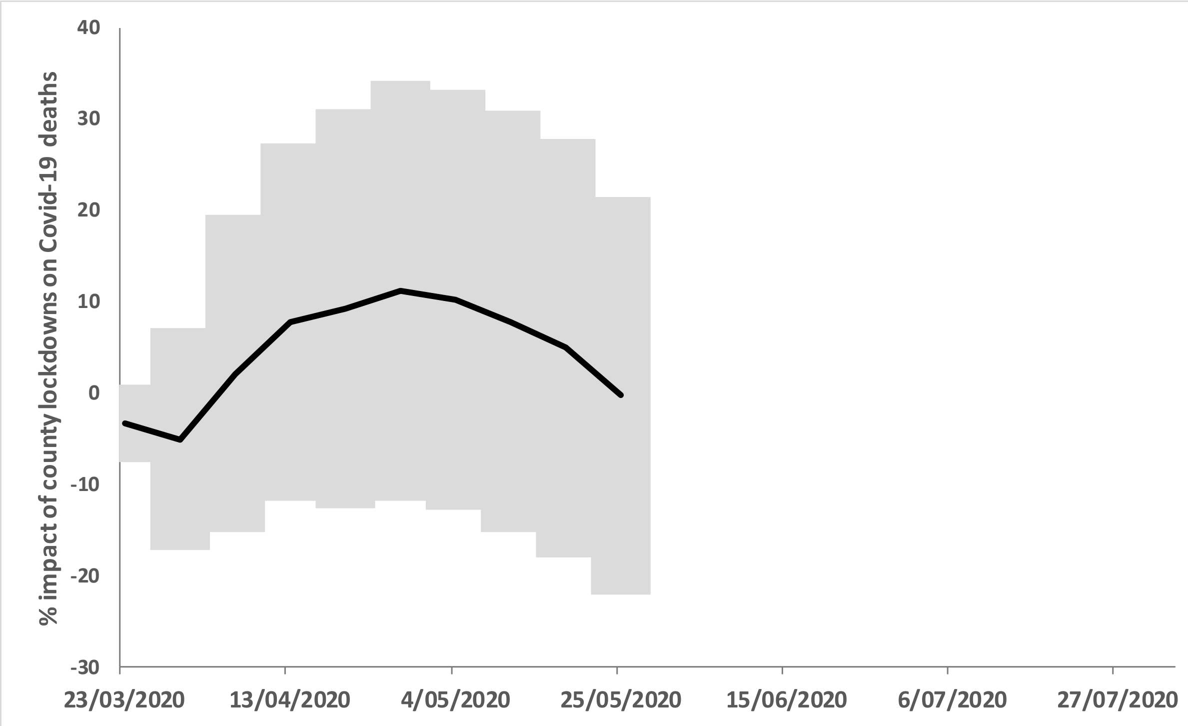
***, **, * denote statistical significance at 1%, 5% and 10% levels

N=3104 US counties.

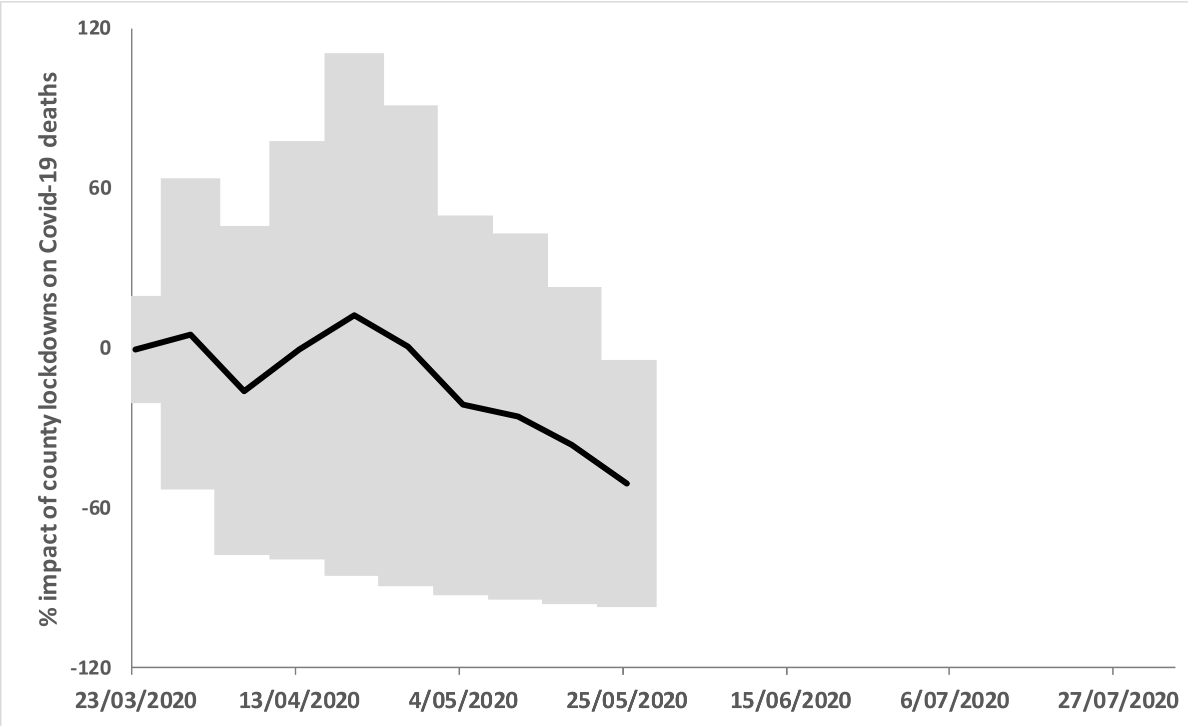
Figure C1: Sensitivity Analyses, Spatial Autoregressive Models with Spatial Errors

Evolving Estimates of the Impact of County Lockdowns on Covid-19 Deaths

(c) Spatial Autoregressive Model
Lockdown Selection on Observations



(d) Spatial Autoregressive Control Function Model
Lockdown Selection on Unobservables



Note
Shaded regions show 95% confidence intervals.