Cyclic strategies to suppress COVID-19 and allow economic activity

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Many countries have applied lockdowns that help suppress COVID-19, but with devastating economic consequences. Here we propose cyclic strategies that provide sustainable, albeit reduced, economic activity. We use mathematical models to show that a cyclic schedule of 4-day work and 10-day lockdown, or similar variants, can, in certain conditions, suppress the epidemic while providing part-time employment. The cycle reduces the effective reproduction number R by a combination of reduced exposure time and an anti-phasing effect in which those infected during work days reach peak infectiousness during lockdown days. The number of work days can be adapted in response to observations. Throughout, full epidemiological measures need to continue including hygiene, physical distancing, compartmentalization and extensive testing and contact tracing. A cyclic strategy is a conceptual framework, which, when combined with other interventions to control the epidemic, can serve as an alternative to full lockdown that offers the beginnings of predictability to many economic sectors.

Non-pharmaceutical interventions to suppress COVID-19 use testing, contact tracing, physical distancing, masks, identification of regional outbreaks, and compartmentalization down to the neighborhood and company level. A major intervention, used in many countries to suppress COVID-19, is population-level quarantine at home known as lockdown[1–4]. The aim is to flatten the infection curve and prevent overload of the medical system until a vaccine becomes available.

Lockdown has a large economic and social cost, including unemployment on a massive scale. It is thus untenable for prolonged periods of time. Many countries therefore reopen the economy by gradually returning sectors to work. However, reopening the economy carries the risk of a resurgence of the epidemic, also called a second wave. An extreme response to a second wave would be to reinstate lockdown, and to lift the lockdown when cases fall below a threshold, and then reinstate lockdown upon a third wave and so on[2,5,6] (Fig 1A,S1). While such strategies can, in principle, prevent healthcare services from becoming overloaded, they lead to economic uncertainty and continue to accumulate cases with each resurgence.

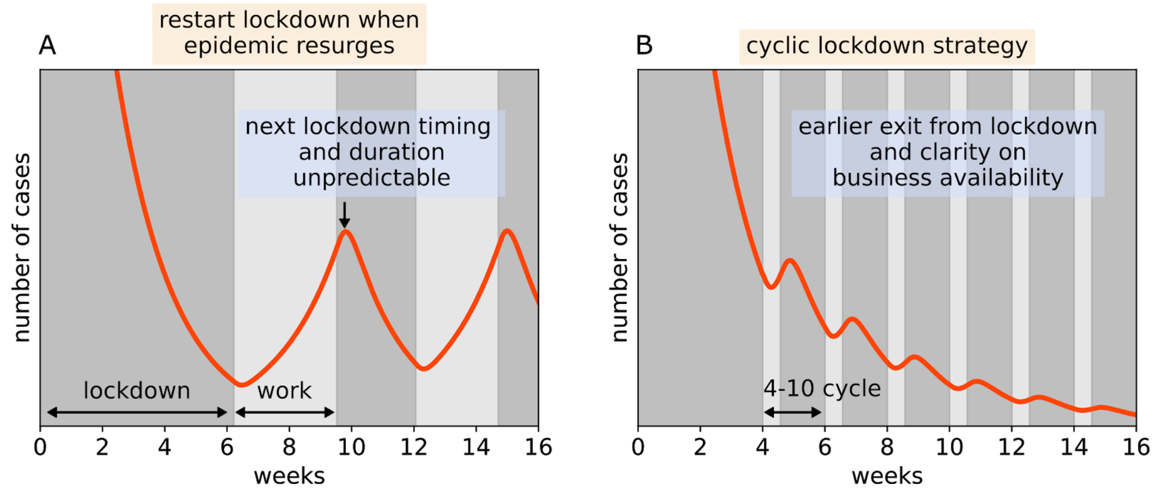

Fig. 1 | Cyclic work-lockdown strategy can control the epidemic, prevent resurgences and offer predictable part-time employment. *a) Exit from lockdown carries the risk of resurgence of the epidemic, with need to re-enter prolonged lockdown. b) A cyclic work-lockdown strategy prevents resurges by keeping the average Re<1. It thus allows an earlier exit from lockdown, and provides a clear part-time work schedule. Transmission rates provide Re in lockdown and work days of* $R_L = 0.6$ *and* $R_W = 1.5$ *respectively. The initial conditions are of low infection rates far from herd immunity, and thus the dynamics is independent of the absolute value on the y axis.*

Here we carefully propose a strategy that can prevent resurgence of the epidemic while allowing predictable and sustained, albeit reduced, economic activity. The strategy can be implemented at a point where lockdown has succeeded in stabilizing the number of daily critical cases to a value that the health system can support. Hereafter when we say 'lockdown' we mean population-level quarantine at home, together with all other available interventions such as masks, quarantine of people with symptoms and physical distancing.

The basic idea is to keep the effective reproduction number Re, defined as the average number of people infected by each infected individual, below 1. When Re is below 1, the number of infected people declines exponentially, a basic principle of epidemiology.

To reduce Re below 1, we propose a cyclic schedule with k continuous days of work followed by n continuous days of lockdown (see also refs [7,8]). As shown below, 4 days of work and 10 days of lockdown is a reasonable cycle that allows a repeating 2-week schedule. Epidemiological measures should be used and improved throughout, including rapid testing, contact isolation and compartmentalization of workplaces and regions. The cyclic strategy can thus be considered as a component of the evolving policy toolkit that can be combined with other interventions.

By "work days" we mean release from lockdown with strict hygiene and physical distancing measures on the same k weekdays for everyone. The nature of the release from lockdown can be tuned. It can include the entire population including schools, except for quarantined infected individuals and people in risk groups who may be in quarantine.

More conservatively, it can include workers in selected sectors of the economy. Remote work should be encouraged for sectors that can work from home.

Recently a cyclic strategy called alternating quarantine was proposed in which the population is divided into two sets of households that work on alternating weeks, namely a 7-work:7-lockdown schedule in two shifts[9]. Here we examine this strategy under varying k, i.e. two groups, each with a k-work:(14-k)-lockdown schedule, working in a staggered manner on alternating weeks (Fig 2, Fig S6). The staggered strategy has the advantage that production lines can work throughout the month, and transmission during workdays is reduced due to lower density (Methods). The non-staggered strategy has the advantage that lockdown days are easier to enforce.

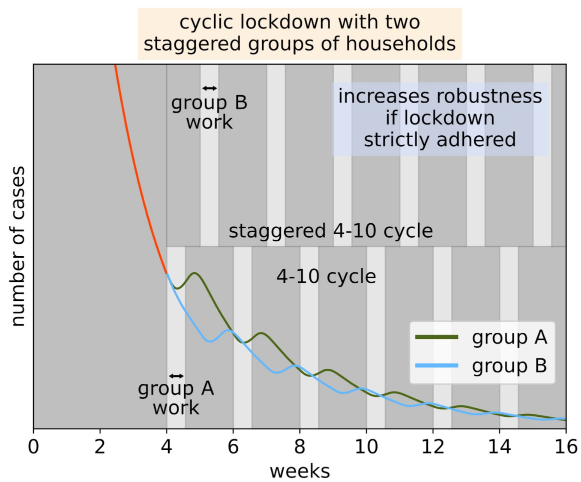

Fig. 2 | Staggered cyclic work-lockdown strategy in which the population is divided into two groups of households that work on alternating weeks. *Shown is I(t) from the SEIR-Erlang deterministic model with mean latent period of 3 days and mean infectious period 4 days* [10,11]*. Transmission rates in lockdown and work give* $R_L = 0.6$ *and* $R_W = 1.5$ *respectively. Density compensation is* $\phi = 1.5$ *and non-compliance is 10% (see Methods).*

The cyclic strategies reduce Re by two effects: *time-restriction* and *anti-phasing*. The time-restriction effect is a reduction in the time T that an infectious person is in contact with many others, compared to the situation with no lockdown[7,8]. For example, a 4-day work: 10-day lockdown cycle reduces T to 2/7 T ≈ 0.3T.

The anti-phasing effect uses the timescales of the virus against itself (Fig. 3). Most infected people are close to peak infectiousness for about 3-5 days, beginning after a latent period of ≈3 days on average after being exposed[12,13]. A proper work-lockdown cycle, such as a 4-work:10-lockdown schedule, allows most of those infected during work days to reach maximal infectiousness during lockdown, and thus avoid infecting many others. Those with significant symptoms can be infectious for longer [13], but remain hospitalized, isolated or quarantined along with their household members, preventing secondary infections outside the household. The wide variation in the latent and infectious periods across people is taken into account in the model. The time-restriction effect is by far the larger of the two effects (Fig. S10).

The cyclic strategy can be synergistically combined with rapid testing and contact isolation. Household-level testing at the end of the lockdown period and before return to work or school can help shorten infection chains.

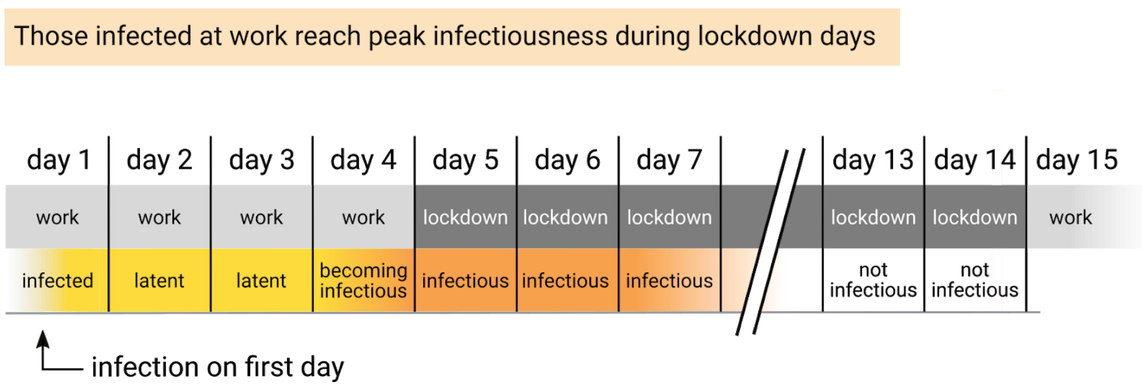

Fig. 3 | The cyclic exit strategy is aided by placing peak infectiousness in the lockdown days. *SARS-CoV-2 has an average latent (non-infectious) period of about 3 days. A 14-day cycle in which people enter lockdown after 3 or 4 work days benefits from this property. Even those infected on the first day of work spend most of their latent period at work and reach peak infectiousness during lockdown. This reduces the number of secondary infections (see Fig. S11)..*

Simulations using a variety of epidemiological models, including SEIR models and stochastic network-based simulations, which include the effect of superspreaders and rapid spreaders through long-tailed distributions of transmission parameters, show that a cyclic strategy can suppress the epidemic provided that the lockdown is effective enough (Fig. 4, Table 1). A 4-10 cycle seems to work well for a range of parameters and is robust to uncertainties in the model (Fig. S2, S3).

To see which cyclic strategy is best in a given situation, one can consider the transmission parameters during work days and lockdown days. These can be described by the effective reproduction numbers that characterize extended periods of work and lockdown conditions, R_W and R_L respectively. Use of effective reproduction numbers has the advantage that it takes into account many factors that affect transmission, including effectiveness of interventions, variation across locations in weather, demography, age-structure, culture etc. The effective reproduction number on workdays R_W encompasses all interactions during workdays (e.g. shopping, community interactions, family visits, etc.), not just interactions during work. In the same manner, R_L includes all interactions during lockdown days, including both interactions with household members as well as interactions of essential workers and of people who do not adhere to the lockdown.

Data for different countries suggest that effective cyclic strategies are possible with realistic reproduction numbers (SI section 1). Lockdown need only be as strong as that achieved in most European countries, with R_L=0.6–0.8[14,15] , in order to support a cyclic strategy with 3-4 work days, when measures during workdays provide $R_W \approx 1.5$ or lower (Table 1, see SI for reproduction number estimates in various countries). Stronger lockdown with $R_L \approx 0.3$ [16,17] and a work-day $R_W = 1.5$ can support up to 7–8 work days per two week cycle (Fig 4B); in this case, a 4-10 cycle can suppress the epidemic even if workday R_W is as large as in the early days of the epidemic, R_W=3–4 [18]. Ideally, measures will eventually bring down Re during workdays below 1, as in South Korea's control of the epidemic in early 2020, making cyclic lockdown unnecessary.

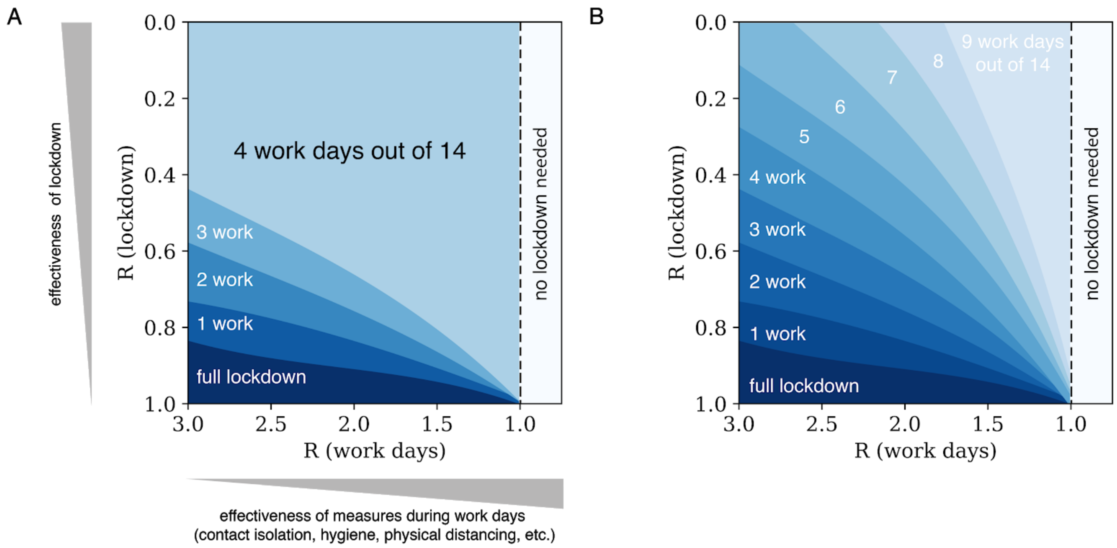

Fig. 4 | Cyclic strategy with k workdays and 14-k lockdown days controls the epidemic for a range of effective replication numbers at work and lockdown. *Each region shows the maximal number of work days in a 14-day cycle that provide decline of the epidemic. Simulation used a SEIR-Erlang deterministic model with mean latent period of 3 days and infectious periods of 4 days. Results are robust to uncertainty in model parameters (Fig S2). (A) strategies with 1-4 workdays every two weeks, 4:14-workday region highlighted (B) k-workday strategies every two weeks, upto k=9.*

Table 1. Effective replication numbers for a 4:10 cyclic strategy in several scenarios. R_W and R_L are the replication numbers that would be observed in continuous periods of work and lockdown, respectively. Parameters and simulations are as in Figs. 1, 3.

R_W	R_L	***Effective replication number , Re, in 4:10 cycle (Re<1 means epidemic declines)***	***Effective replication number , Re, in 4:10 cycle with two staggered groups***
1.5	***0.6***	***0.86***	***0.85***
2.0	***0.6***	***0.94***	***0.93***
2.5	***0.6***	***1.03***	***1.02***

2.5	***0.3***	***0.8***	***0.8***

An important consideration is that the cyclic strategy is adaptive, and can be tuned when conditions change and the effects of the approach are monitored. For example, changes in behavior affect transmission, as do heterogeneity and stochastic effects [8], advances in regional monitoring and contact tracing, weather conditions [5,6] and other factors. If one detects, for example, that a 4:10 strategy leads to an increasing trend in cases (e.g. as winter approaches), one can shift to a cycle with fewer work days. Conversely, if a strong decreasing trend is observed, one can shift to more work days and gain economic benefit (Fig 5) while still suppressing the epidemic. In certain scenarios, 6-8 days of work or more in two weeks can be achieved [19] (Fig S3, Fig S8). Generally, changes in work and lockdown transmission (R_W and R_L) have only a mild effect on the Re in the cyclic strategy, as shown in Fig S7.

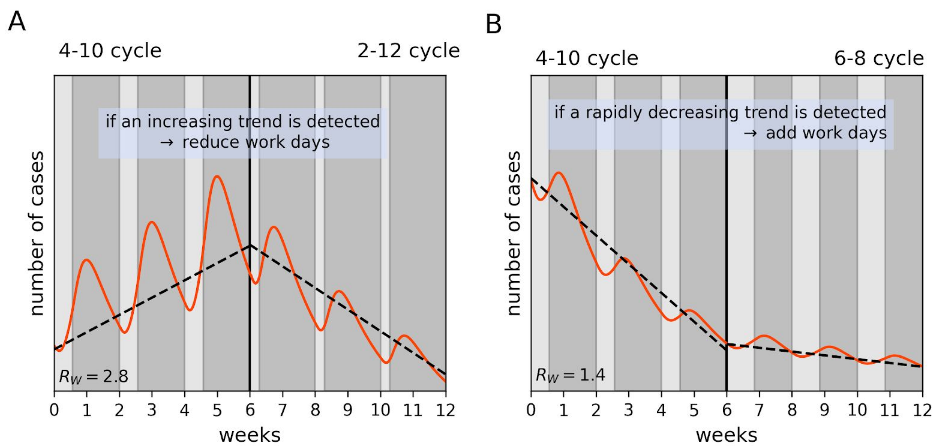

Fig. 5 | The cyclic strategy can be tuned according to the trends in case numbers over weeks. *(a) If average Re is above 1, cases will show a rising trend, and number of work days in the cycle can be reduced to achieve control. (b) Number of work days per cycle can be increased when control meets a desired health goal.*

Measures will be required during the work days to ensure that people do not excessively compensate for the lockdown periods by having so many more social connections that R is significantly increased. This may include sound epidemiological measures such as the continuation of banning large social gatherings which have risk of superspreader events [20–22] and clear communication campaigns by the health authorities to enhance adherence to hygiene and physical distancing. Rapid testing and contact tracing should be developed and extended in parallel[23].

The economic benefits of a cyclic strategy include part-time employment to millions who have been put on leave without pay or who have lost their jobs. This mitigates massive unemployment and business bankruptcy during lockdown. Prolonged unemployment and the recession that is expected to follow can reduce worker skill [24–28] and slow down the return to work for many of the unemployed, in addition to major societal drawbacks [25]. Unemployment also has detrimental health effects which include exacerbation of existing physical and mental illnesses.

The cyclic strategy offers a measure of economic predictability, potentially enhancing consumer and investor confidence in the economy which is essential for growth and recovery[29]. It can also be equitable and transparent in terms of who gets to exit lockdown.

For these reasons, a cyclic strategy can be maintained for far longer than continuous lockdown. This allows time for developing a vaccine, treatment and effective testing without overwhelming health care capacity.

Not all economic sectors stand to benefit equally from a cyclic strategy. Sectors with high fixed costs or high risk of transmission, including restaurants, hotels and businesses based on large events, will require special adjustments, as in any exit strategy. Sectors that allow for partial remote work can thrive. Productivity during the work days can be increased by prolonged hours and work in shifts. Since regions differ, it would be important to perform detailed economic analyses of cyclic strategies in each setting.

The cyclic strategy does not seem to have a long-term cost in terms of COVID-19 cases compared to reopening society and locking it down again with every resurgence wave. The crucial point is that the cyclic strategy keeps average Re below one, exponentially reducing cases and preventing resurgences. In contrast, a reopening strategy that restarts lockdown with every resurgence effectively keeps Re close to 1, by a form of feedback, and therefore continues to accumulate cases. Comparing the two strategies shows that in the mid-term and long term, the reopening-reclosing strategy accumulates more cases due to resurgences than the cyclic strategy (Fig. 6). This does not depend heavily on parameters: the fundamental reason is that new cases arise during each resurgence.

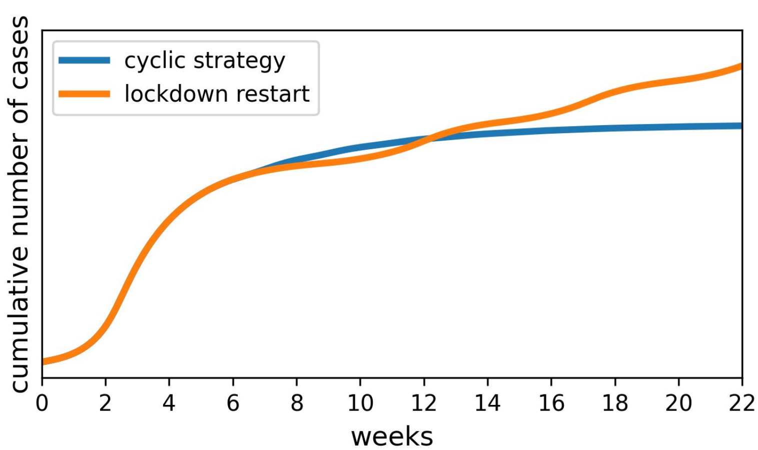

Fig. 6 | The cumulative number of cases under a cyclic strategy is lower at long times than in a strategy that restarts lockdown when the epidemic resurges. *Cumulative number of cases is shown for the simulations of Fig, 1A (red) and Fig. 1B (blue). Even though exit from lockdown occurred earlier in the* *cyclic strategy case, the cumulative number of cases associated with this strategy is lower in the long term than the accumulated cases when lockdown is released and then restarted once the epidemic resurges. The relative benefit of the cyclic strategy is further increased by considering non-COVID-19-related health consequences of extended lockdown during resurgences, prevented by the cyclic strategy.*

The cyclic strategy can apply in principle at many scales: to a company, a school, a town or an entire country. For examples of adoption of cyclic strategies announced at some of these scales, including firms like MasterCard, the Austrian school system and a region-wide policy in Mexico, see implementation details in SI section 2. Regions or organizations that adopt this strategy are predicted to resist infections from the outside. An infection entering from the outside cannot spread widely because average $R<1$. After enough time, if this is applied globally, there is even a possibility for the epidemic to be eradicated, in the absence of mutations or unknown reservoirs.

The cyclic strategy is not predicated on massive testing and can work in regions with insufficient testing capacity. In regions with a large informal sector, adhering to continuous lockdown may be untenable. This may apply to a large part of the Earth's population. A cyclic strategy provides economic opportunity during work days that may hypothetically improve adherence during lockdown days.

The cyclic strategy has several caveats. It can not suppress the epidemic if the reproduction number during lockdown days is larger than one. The strategy is less effective the larger the fraction of transmissions which are very rapid, as opposed to transmissions whose probability is nearly proportional to exposure time (Methods). Avoiding large events with potential for rapid transmission is thus important. Since many unknowns remain for modelling this epidemic, monitoring is required after implementation of a cyclic strategy (as in Fig 5).

With these considerations in mind, a cyclic strategy can serve as a less risky step than full reopening of the economy and can thus be tried earlier to minimize damage caused by lockdown. The exact nature of the intervention can be tuned to optimize economic and social outcomes and minimize infection in each region and situation. It can be tested for a limited duration such as a month, and in a limited region. The cyclic strategy can be synergistically combined with other approaches to suppress the epidemic and address the economic crisis.

Methods

SEIR model: The deterministic SEIR model is $dS/dt = -\beta SI, dE/dt = \beta SI - \sigma E, \ dI/dt = \sigma E - \gamma I$, where S, E and I are the susceptible, exposed (noninfectious) and infectious fractions. Reference parameters for COVID-19 [10] are $\sigma = \frac{1}{3}$ day^{-1}; $\gamma = \frac{1}{4}$ day^{-1}, and S=1 is used to model situations far from herd immunity. The values used for β are defined in each plot by $Re = \beta/\gamma$. The analytical solution for cyclic strategies is in (SI).

SEIR-Erlang model: The SEIR model describes an exponential distribution of the lifetimes of the exposed and infectious compartments. In reality these distributions show a mode near the mean. To describe this, we split E and I into two artificial serial compartments each with half the mean lifetime of the original compartment [30]. This describes Erlang-distributed lifetimes (the distribution of the sum of two exponentially distributed random variables) with the same mean transition rates as the original SEIR model. Thus, $dS/dt = -\beta SI, \ dE_1/dt = \beta SI - 2\sigma E_1, dE_2/dt = 2\sigma E_1 - 2\sigma E_2, \ dI_1/dt = 2\sigma E_2 - 2\gamma I_1, \ dI_2/dt = 2\gamma I_1 - 2\gamma I_2$, where $I = I_1 + I_2$, and $Re = \beta/\gamma$. In the figures we used a worst-case assumption of no herd immunity, namely $S \approx 1$. Approach towards herd immunity further reduces case numbers. Case numbers are in arbitrary units, and can describe large or small outbreaks. The deterministic simulation describes a fully-mixed population. Population structure typically reduces overall outbreak peak size [31] compared to a fully mixed situation with the same mean transmission rate, but includes the possibility of high attack rates in certain sub-populations. For example, a stochastic simulation on a network shows a larger range of conditions for a cyclic strategy to work than in a deterministic model (compare Fig. 4 and Fig. S5).

Staggered cyclic strategy, SEIR-Erlang model: We model two groups, A and B, with a susceptible, exposed and infectious compartment for each group. The SEIR-Erlang model for group A is:

$$dS_A/dt = -f_A(S_A, I_A, t)$$
$$dE_{A,1}/dt = f_A(S_A, I_A, t) - 2\sigma E_{A,1}$$
$$dE_{A,2}/dt = 2\sigma E_{A,1} - 2\sigma E_{A,2}$$
$$dI_{A,1}/dt = 2\sigma E_{A,2} - 2\gamma I_{A,1}$$
$$dI_{A,2}/dt = 2\gamma I_{A,1} - 2\gamma I_{A,2}$$
$$I_{A,tot} = I_{A,1} + I_{A,2}$$

with analogous equations for group B. We assume that each group consists of half of the population. This causes density at work to be reduced [9]. For ease of comparison to the non-staggered case, we refer to the replication numbers of a single fully mixed population with a cyclic strategy, namely $Re = R_W$ on work days and $Re = R_L$ during lockdown. In the staggered case, during lockdown, as opposed to work, individuals from a group interact primarily with their own household. The density in the household is not affected by dividing the population into two staggered work groups. Hence, Re remains R_L.

$$f_A(S_A, I_A, t = A\ lockdown\ day) = 2R_L \gamma S_A I_A$$

Where the factor of 2 normalizes $S_A = 0.5$. During work days, we can estimate the number of transmissions at work and not at home by $R_W - R_L$. This gives the following equation:

$$f_A(S_A, I_A, t = A\ work\ day) = (2R_L + (R_W - R_L))\gamma S_A I_A$$

With analogous equations for group B.

We next model cross-transmission between the groups. Due to the expected difficulty of enforcing a staggered work schedule as compared to a non-staggered cycle strategy, we assume a leakage term due to a fraction of individuals ρ from each group that does not adhere to their lockdown. These non-adherers instead interact with the other group during the other groups' work days.

When group B is in lockdown, infectious non-adherers from group B can infect individuals from group A who are in their work days. This rate is modeled as proportional to the replication number for people infected at work and not at home, $R_W - R_L$:

$$f_A(S_A, I_A, S_B, I_B, t = A\ work\ day,\ B\ lockdown\ day) = (2R_L + (R_W - R_L))\gamma S_A I_A + \rho(R_W - R_L)\gamma S_A I_B$$

When individuals from group A are in lockdown and non-adhere, they can be infected from individuals from group B on group B work days. We also add a higher-order term for susceptible non-adherent individuals from group A that meet non-adherent infectious individuals from group A during group A lockdown:

$$f_A(S_A, I_A, t = A\ lockdown\ day,\ B\ work\ day) = 2R_L \gamma S_A I_A + \rho(R_W - R_L)\gamma S_A I_B + \rho^2(R_W - R_L)\gamma S_A I_A$$

When both groups are in lockdown at the same time, there is no leakage:

$$f_A(S_A, I_A, t = A\ lockdown\ day,\ B\ lockdown\ day) = 2R_L \gamma S_A I_A$$

Note that for complete leakage $\rho = 1$ and under symmetry assumptions $I_1 = I_2$, the equations become identical to the case of a single fully mixed population:

$$f_A(S_A, I_A, S_B, I_B, t = A\ work\ day) = 2R_W \gamma S_A I_A$$

$$f_A(S_A, I_A, S_B, I_B, t = A\ lockdown\ day) = 2R_L \gamma S_A I_A$$

So far, we assumed that density at work is half that of the non-staggered case. However, in practice, compensatory mechanisms might lead to a higher effective density. For example, people might cluster to maintain a level of social interaction, or certain work-day situations may require a fixed density of individuals. These effects can be modeled by adding a density compensation parameter ϕ which rescales the work-day infection rate. This number is $\phi = 2$ for complete compensation of transmission where density at work is not affected by partitioning, or $\phi = 1$ is the staggered model above with half the density at work. We obtain the following equations:

$$f_1(S_A, I_A, S_B, I_B, t = A\ work\ day,\ B\ lockdown\ day) = (2R_L + \phi(R_W - R_L))\gamma S_A I_A + \rho\phi(R_W - R_L)\gamma S_A I_B$$

$$f_1(S_A, I_A, t = A\ lockdown\ day,\ B\ work\ day) = 2R_L\gamma S_A I_A + \rho\phi(R_W - R_L)\gamma S_A I_B + \rho^2\phi(R_W - R_L)\gamma S_A I_A$$

With analogous equations for group B.

Linearity of transmission risk with exposure time: In order for restriction of exposure time to be effective, the probability of infection must drop appreciably when exposure time is reduced. This requires a low average infection probability per unit time per social contact, q, so that the probability of infection, $p = 1 - exp(-qT)$, does not come close to $p=1$ for exposure time T on the order of days. For COVID-19, when no safety measures are taken, an infected person infects on the order of R=3 people on average during the infectious period of mean duration D=4 days. If the mean number of social contacts is C, which is estimated at greater than 10, one has $q \sim DR/C < 0.1/day$. Thus, in this rough estimate, infection probability on the scale of hours to a few days is approximately linear with exposure time: $1 - exp(-qT) \approx qT$. This is consistent with the observation that infected people do not typically infect their entire household, but instead show attack rates on the order of 0.1-0.3 [32–35]. It also matches the linearity observed in influenza transmission[36]. We also tested a scenario using network models in which some contacts have much higher q than others (exponentially distributed q between links). A mildly lower R in lockdown is required to provide a given benefit of the cyclic strategy than when q is the same for all links. This suggests that a fraction of rapid spreading interactions do not make a large difference as long as the mean transmission is close to linear. We note that there is evidence of rapid super-spreading events, as in a study of a choir practice [21]. If such rapid transmissions constitute a large enough share of the transmissions in a given region, the linearity assumption may not apply, and the cyclic strategy effectiveness could be decreased.

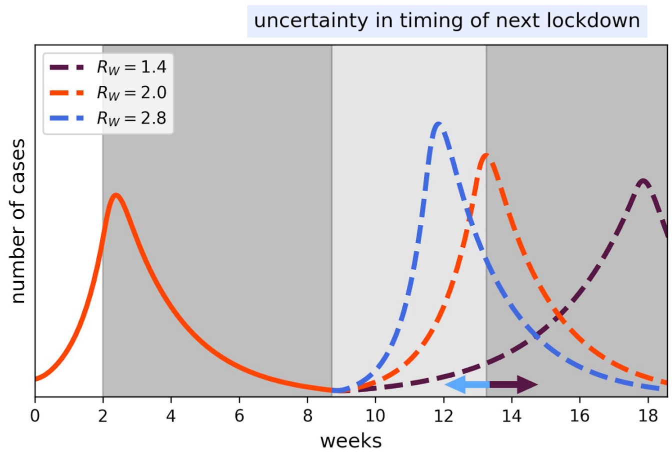

Fig. S1. Reinstating lockdown based on case number threshold leads to uncertainty in the timing of new lockdown. *SEIR-Erlang model simulation showing the initial growth phase of an epidemic in the first two weeks, triggering a lockdown of 7 weeks. Lockdown is reinstated once a threshold of cases is exceeded. We show three scenarios with different effective reproduction numbers after lockdown is first lifted (R_W=1.4, R_W=2.0 and R_W=2.8), leading to a wide distribution of the time at which the case threshold is crossed and lockdown is reinstated.*

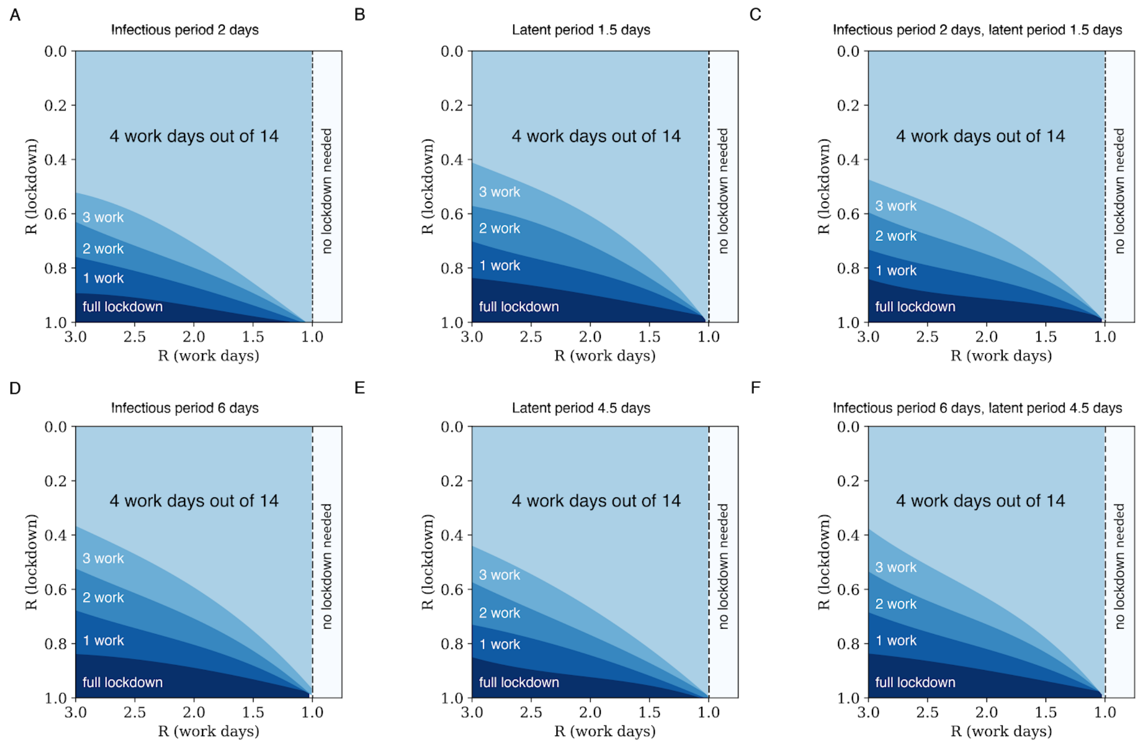

Fig S2. The cyclic strategy is insensitive to variations in the model parameters. *The SEIR-Erlang model has two free parameters, the lifetimes of the latent and infectious periods, given by* $T_E = 1/\sigma$ *and* $T_I = 1/\gamma$. *The reference parameters used in the main text are* T_E*=3 days, and* T_I*=4 days based on COVID-19 studies* [10,11]*. The panels show the regions in which Re<1 with (A)* T_E*=3d and* T_I*=2d, (B)* T_E*=1.5d and* T_I*=4d, (C)* T_E*=1.5d and* T_I*=2d, (D)* T_E*=3d and* T_I*=6d, (E)* T_E*=4.5 d and* T_I*=4d, and (F)* T_I*=6d,* T_E*=4.5 d. These and similar parameter variations make small differences to the phase plots.*

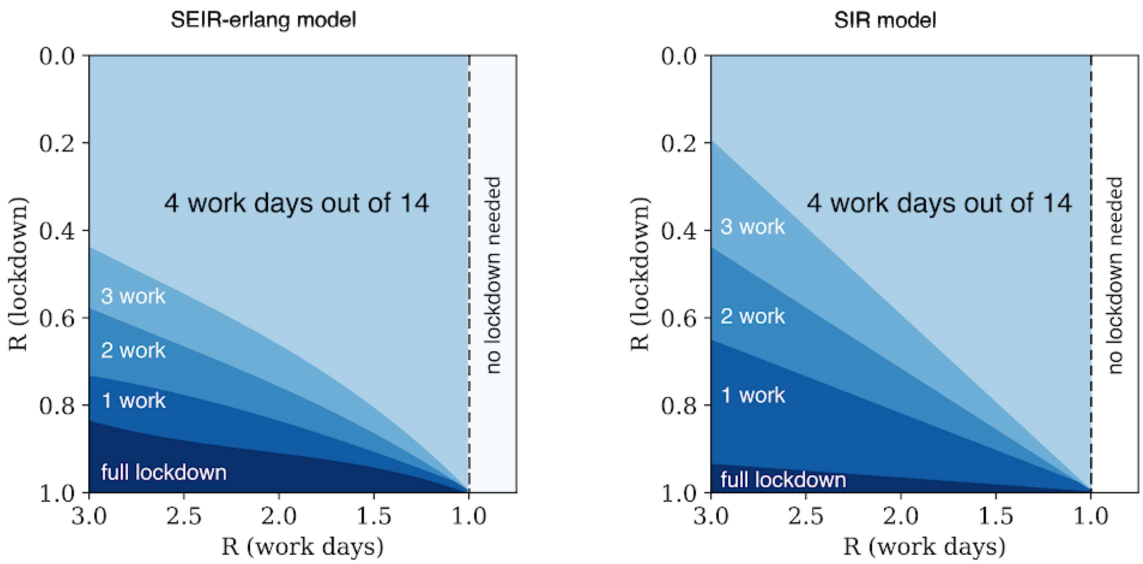

Fig. S3 A SIR deterministic model captures some of the effects. *The SIR model (right panel) lacks the exposed (non-infectious) compartment. It shows that the cyclic lockdown strategies can control the epidemic, but at smaller parameter regions for each given strategy than the SEIR-Erlang model (left panel). The difference is biggest at large ratios of R at work and lockdown, where SEIR-Erlang has an advantage. The SIR model is* $dS/dt = -\beta SI, dI/dt = \beta SI - \gamma I$*. The value of* γ *does not affect the plot. We used S=1. Effective Re in the SIR model is the weighted average of* R_W *and* R_L*, weighted by the fraction of time at work and lockdown. For analytical work on optimal epidemic control in the SIR model see [https://osf.io/rq5ct/].*

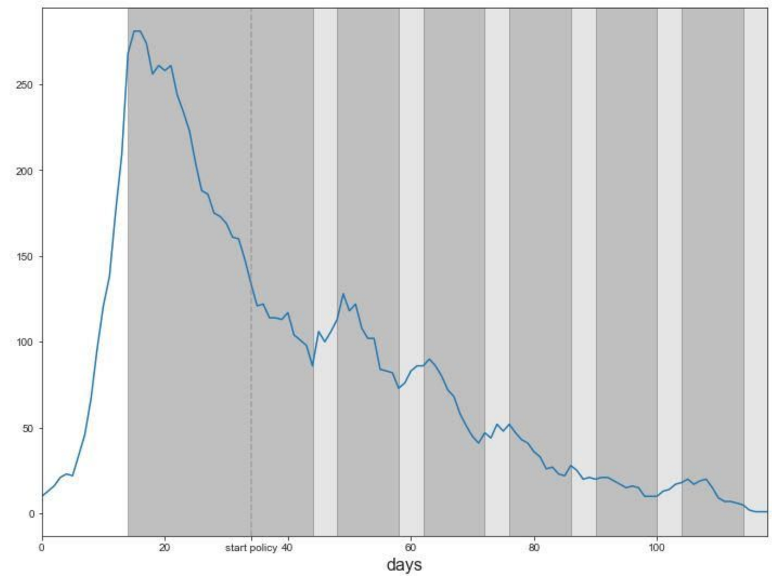

Fig. S4. *Stochastic simulation of a 4-work-10-lockdown cyclic strategy using a SEIR process simulated on a contact network. Infected nodes versus time from a simulation run using the SEIRSplus package from the Bergstrom lab, https://github.com/ryansmcgee/seirsplus. Contact network has a power-law-like degree distribution with two exponential tails, with mean degree of 15, N=10^4 nodes, sigma=gamma=1/3.5 days, beta=0.95 till day 14, lockdown beta=0.5 with mean degree 2 (same edges removed every lockdown period), work day beta=0.7. Probability of meeting a non-adjacent node randomly at each time-step instead of a neighbor node is p=1 before day 14, in lockdown p=0, workday p=0.3. Testing is modeled to quarantine 1% of infected nodes per day, with no contact tracing. Shaded regions are lockdown periods, light gray regions are workdays. Initial conditions were 10 exposed and 10 infected nodes.*

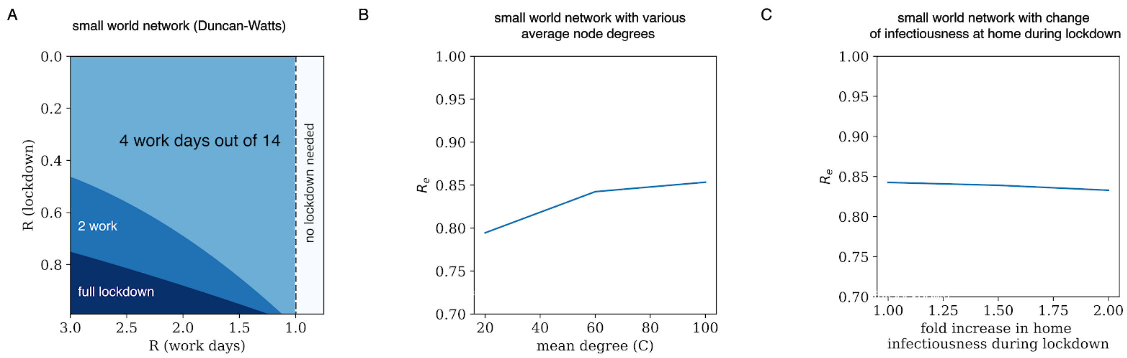

Fig S5. A stochastic simulation on a small-world network shows a similar range in which the epidemic is controlled by a cyclic strategy. *(A) A custom simulator uses a stochastic SEIR process on a social network. The social network is small-world with with* $N = 10000$*, mean degree C=50 and fraction of long-range connections* $p = 1 - R_L / R_W$*. Time-steps are one day. In work days transmission occurs along edges, with probability* $q_W = R_W / (C\ T_I)$*. In lockdown days, the long-range links of each node are inactivated (the same links are inactivated every day), with remaining links signifying the household. Transitions between exposed, infectious and removed states are determined by Erlang (shape=2) distributed times determined for each node at the beginning of the simulation. (BCD) Sensitivity analysis for network simulations. For each case tested, we keep the effective* R_W, R_L *as* $R_L = 0.6$ *and* $R_W = 1.5$ *for the first two weeks. (B) Sensitivity analysis for the mean degree C. (C) Sensitivity analysis for increased infectiousness at home during lockdown, where* q_L *is increased. This requires adjusting the fraction of long-range connections* p *in order to keep Rl=0.6.*

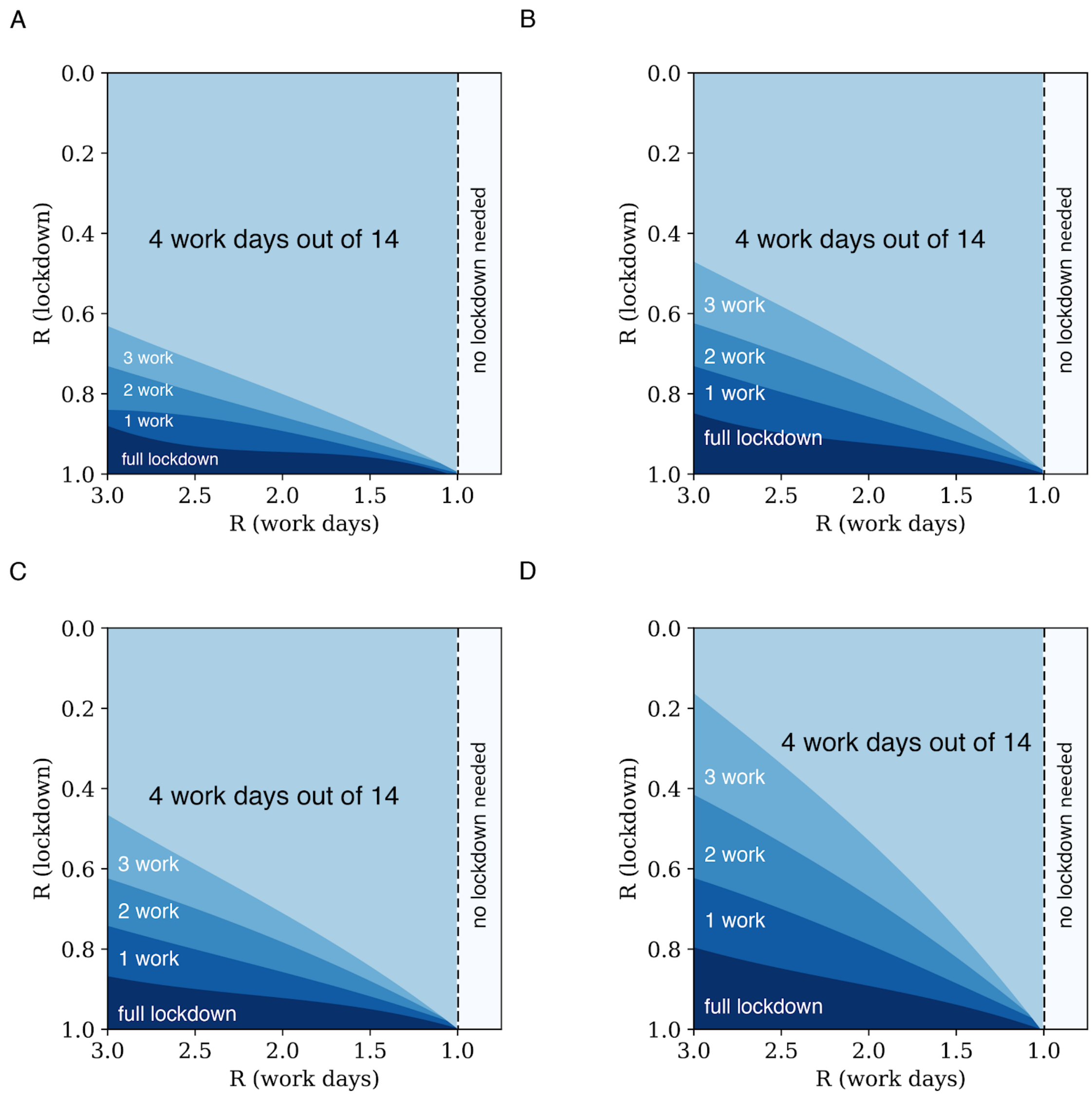

Fig S6. Staggered cyclic strategies control the epidemic for various degrees of density compensation and non-compliance. *Each region shows the maximal number of work days in a 14-day cycle that provide decline of the epidemic. Simulation used a SEIR-Erlang deterministic model with mean latent period of 3 days and infectious periods of 4 days. Density compensation φ and non-compliance (cross transmission) η parameters were as follows: (a) φ=1,η=0.1 (b) φ=1.5,η=0.1 (c) φ=1,η=0.3 (d) φ=1.5,η=0.3. Code can be found at https://github.com/omerka-weizmann/2_day_workweek.*

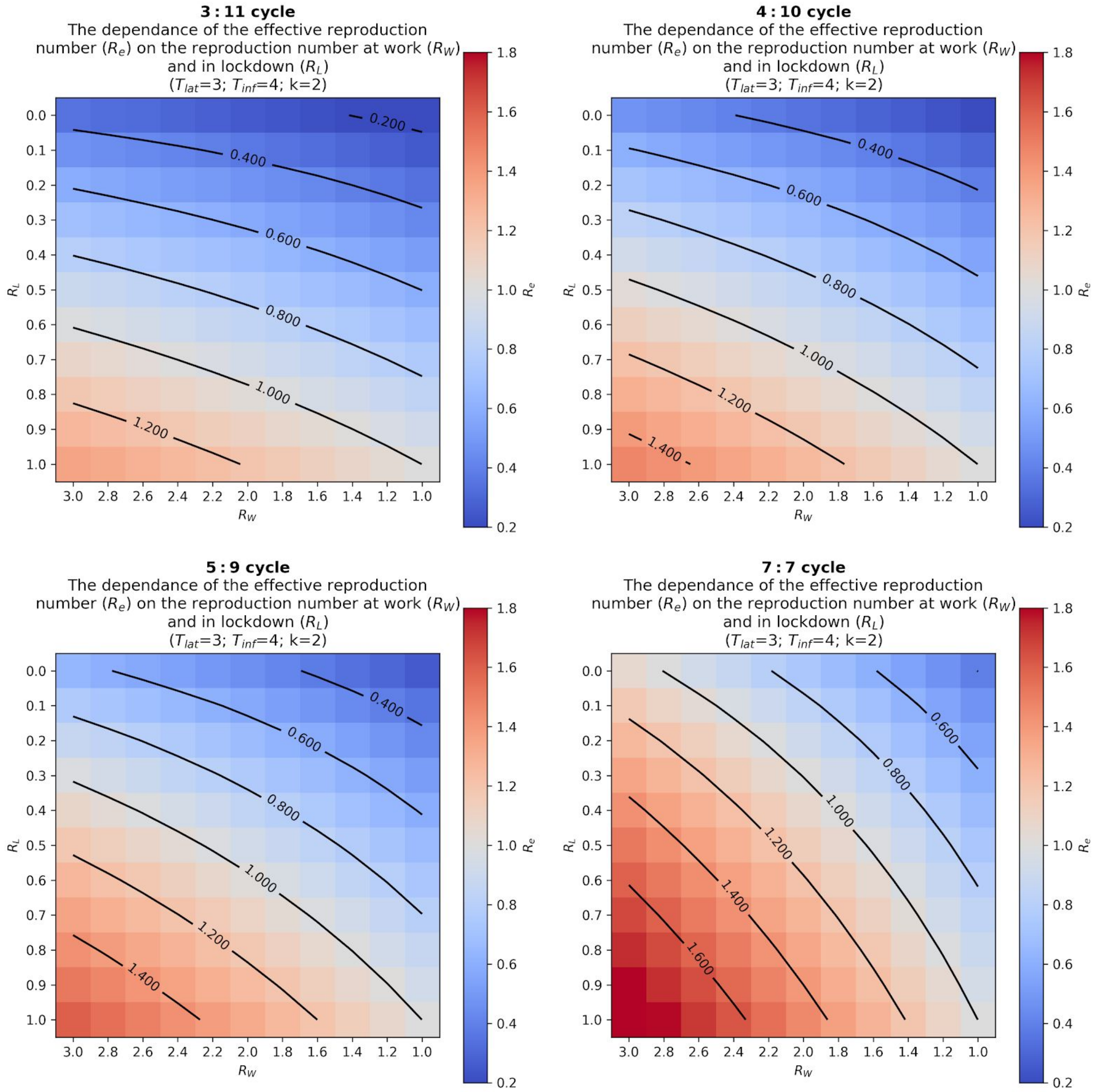

Fig S7. The effective reproduction number Re for different work:lockdown cycles. *The R_e values are computed by the SEIR-Erlang deterministic model with parameters of Fig. 1b. Note that R_e changes gradually, so that if R_W and R_L change slightly, the effects on R_e are mild.*

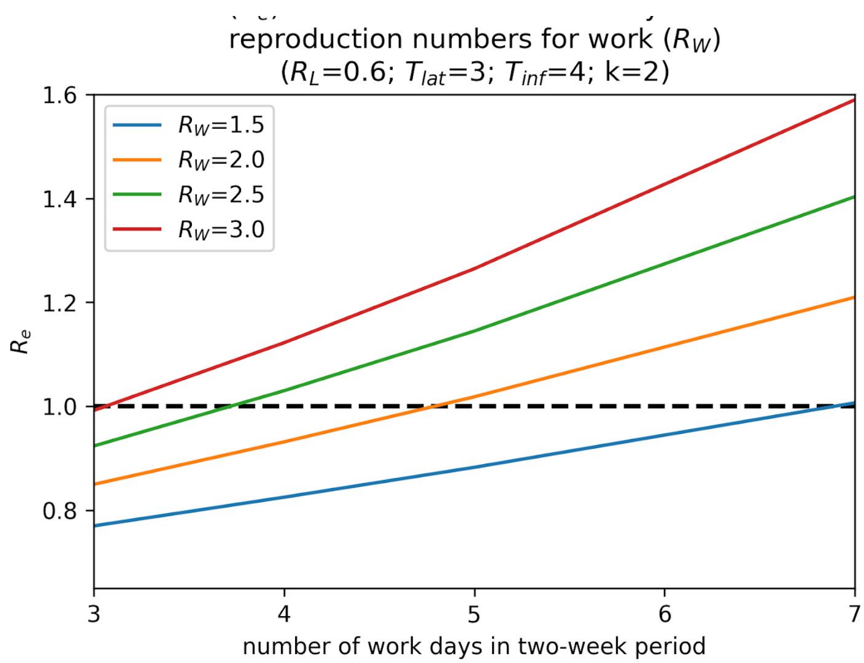

Fig S8. Effective reproduction number grows with the number of work days in a two week period*. It declines with the stringency of work-day measures (lower R_W). From SEIR-Erlang simulations with parameters of Fig 1b.*

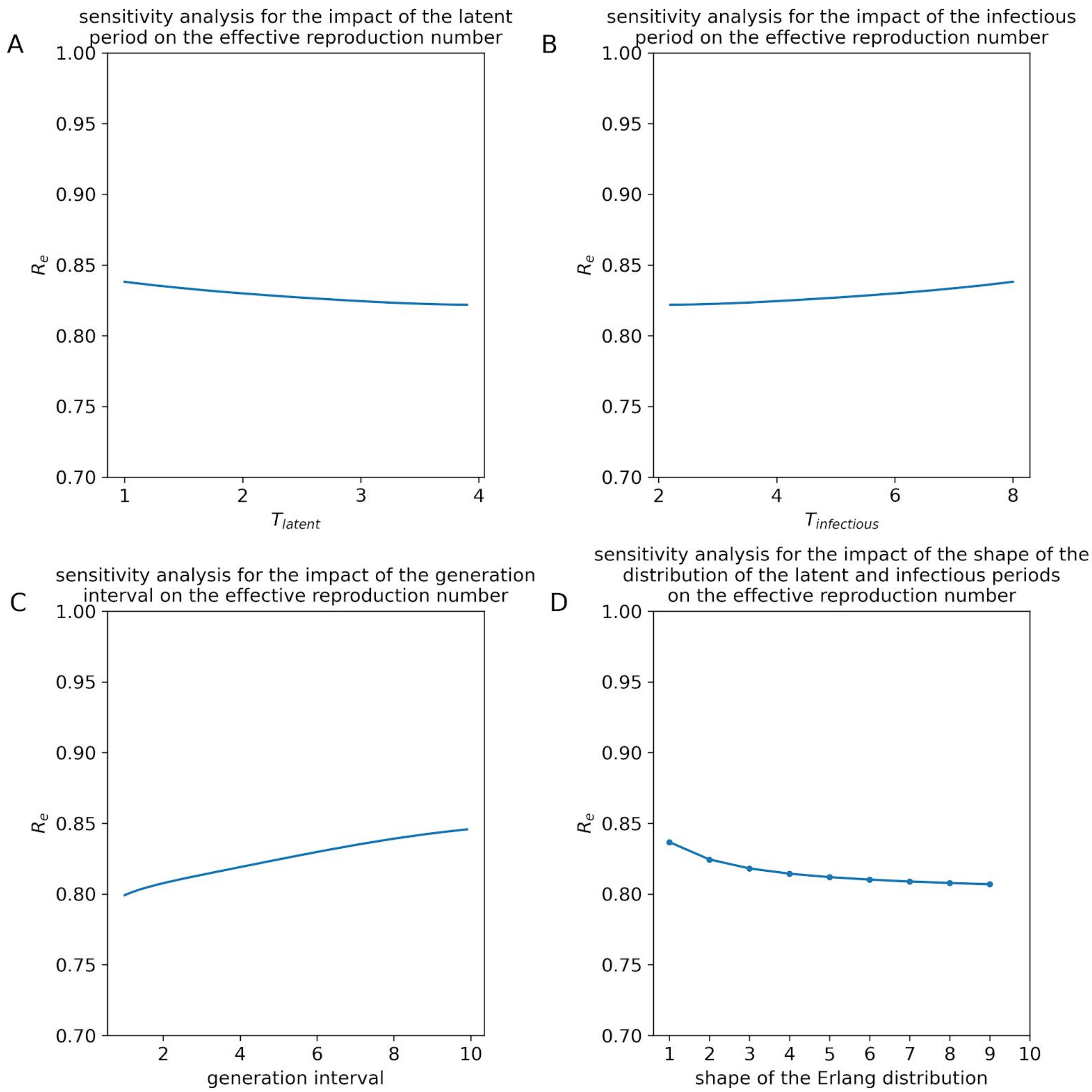

Fig S9. Sensitivity analysis for the effective reproduction number of the cyclic strategy as a function of different model parameters*. Analyses are for a 4:10 cyclic strategy with R_W=1.5 and R_L=0.6.* ***A-B****. Mean duration latent period (A) and infectious period (B) keeping the mean generation interval at 5 days using the relation: generation interval = latent period + 0.5 infectious period.* ***C****. Mean generation interval assuming a ratio between the latent period and infectious period of 3:4.* ***D****. Shape of the Erlang distribution, and hence the standard deviation of the latent and infectious period distributions. The relationship between the standard deviation of the Erlang distribution and its shape is* $\sigma = \frac{\mu}{\sqrt{k}}$ *where μ is the mean of the distribution and k is the shape of the distribution.*

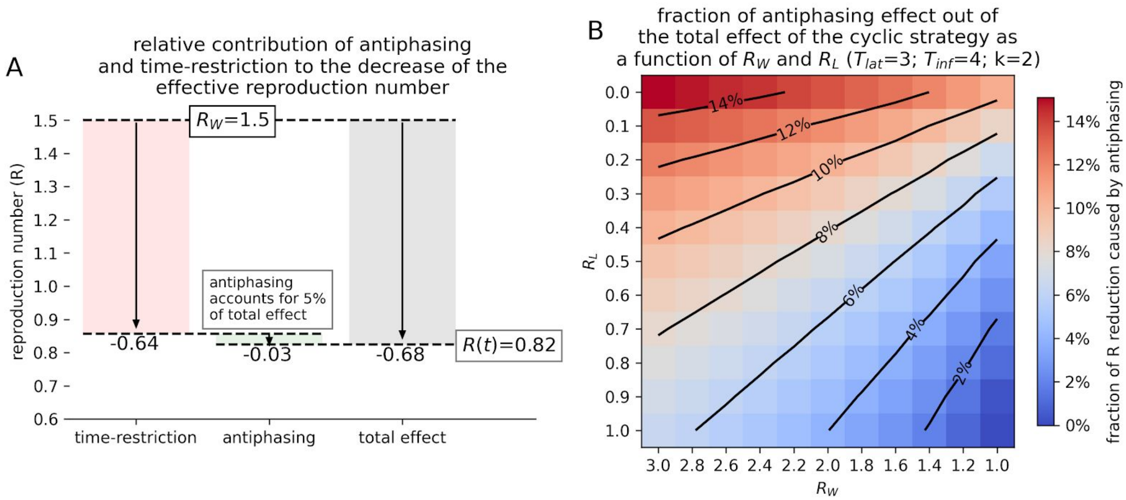

Fig S10. The relative effects of time-restriction and anti-phasing on the effective reproduction number. ***A.*** *The reduction in the effective reproduction number due to time-restriction and anti-phasing in a 4:10 cycle when* R_W*=1.5 and* R_L*=0.6.* ***B.*** *The fraction of the reduction in R due to anti-phasing in a 4:10 cycle with various* R_W *and* R_L *values.*

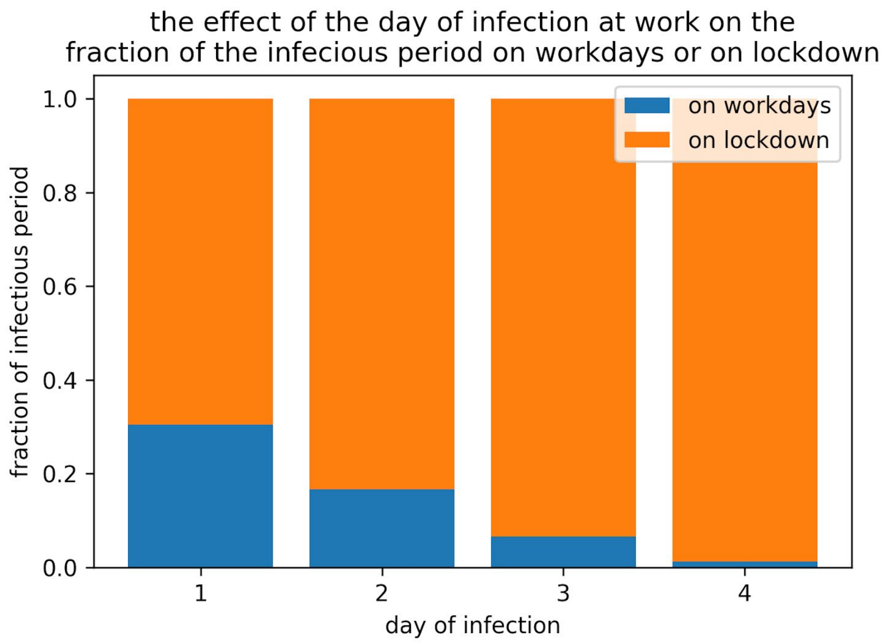

Fig S11. The effect of the day at which a person was infected at work on the fraction of the infectious period spent in the remaining work days*. We assume a 4:10 cyclic strategy with generation time distribution as described in [37] and quantify the fraction of the infectious period that a person spends in workdays (blue) as a function of the day of infection in the 4 workday sequence. The remainder is the fraction spent in the subsequent lockdown days (orange). This figure is complementary to Fig. 3.*

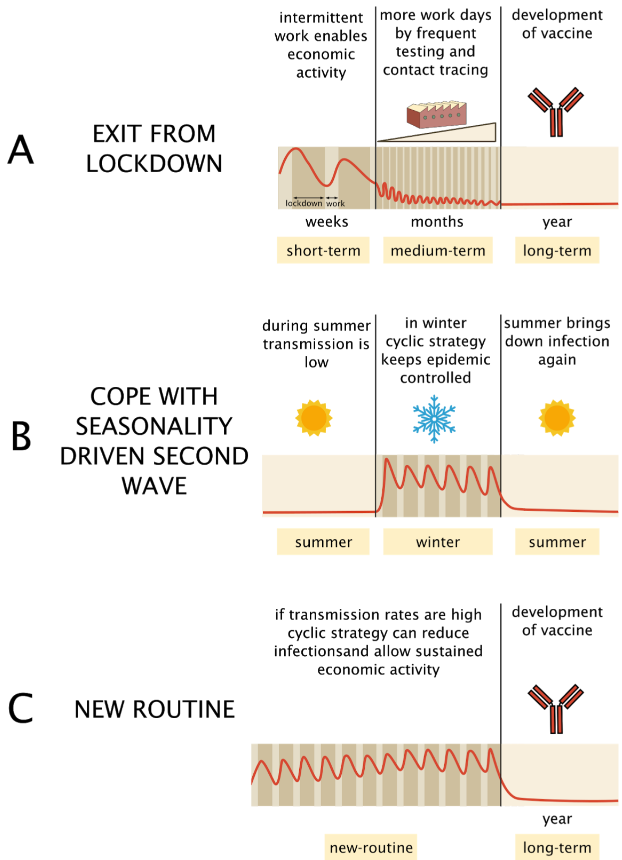

Fig. S12. Different use cases for adopting a cyclic lockdown strategy.

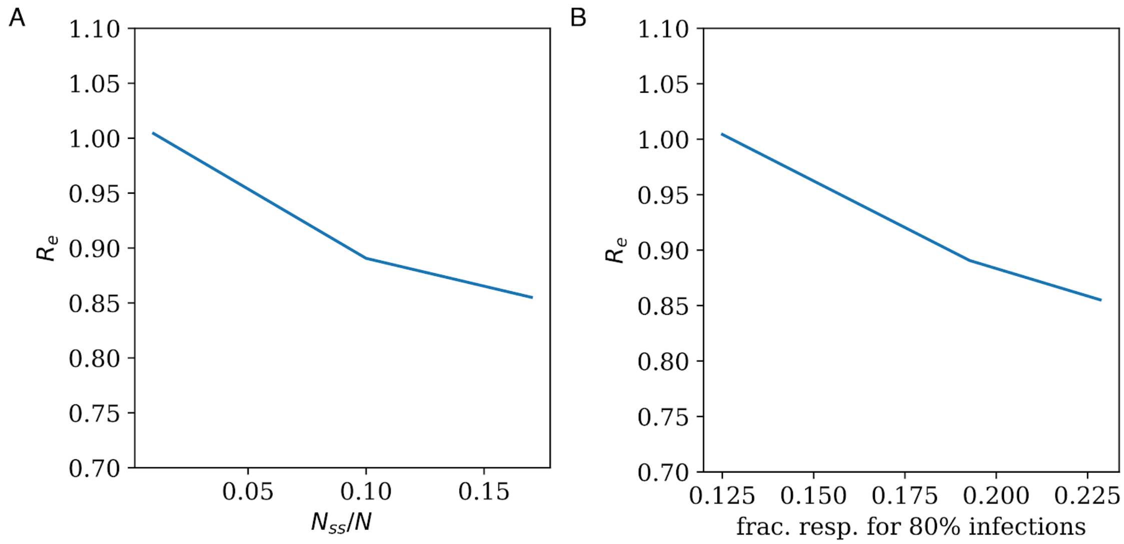

Fig. S13. Effect of super-spreaders on cyclic strategies. *To model individuals that are both highly infectious and have many connections, we adapted the network simulations described in Figure S5 as follows. The network is a directed small-world network with N=10,000 nodes, with each node having a degree k=10: 4 short-range connections and 6 long-range connections. A subset N_{SS} of nodes (the super-spreaders) have an additional 90 outgoing long-range connections. Additionally, the infection rate on superspreader node outgoing edges (q_{SS}) is much larger than other nodes ($q_{ss} >> q$). The number of superspreader nodes was changed, and q was constant (q=0.015 per day), while q_{SS} was set to give Rw=1.5. As in Figure S5, only short range connections are active during lockdown, and, in order to obtain R_L =0.6, infectiousness during lockdown days was increased by a factor of 4.7 per edge. All other simulation details are the same as in Figure S5A. We considered three cases. The most extreme case is that N_{ss} is 1% of all nodes and q_{ss}=0.75 per day, which means that after 4 days (average infectiousness period) all neighbors of the super-spreaders are almost certainly infected (99.6% infection probability). In this case, 80% of all infections during the work period are caused by only 12% of infected individuals. The other cases are N_{ss} = 10%,q_{SS}=0.025 per day and N_{ss} = 17%, q_{SS}=0.015 per day, where in the latter case super-spreading is only due to having much more connections.*

SI Section 1: Estimated reproduction numbers in lockdown and at work for various countries

A list of estimated reproduction numbers from selected countries based on publications, as well as an analysis done for this study, can be found in this updating document.

SI Section 2: Announced adoptions of cyclic exit strategies

A selected list of adoptions on the scale of companies, medical settings, school systems and regions can be found in this updating document.

SI Section 3: Economic perspective on cyclic strategies for COVID19 **can be found in this document**

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