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COVID-19 Pandemic and Economic Scenarios for Ontario*

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Abstract

To study the efficacy of the public policy response to the COVID-19 pandemic, we develop a model of the rich interactions between epidemiology and socioeconomic choices. Preferences feature a "fear of death" that lead individuals to reduce their social activity and work time in the face of the pandemic. The aggregate effect of these reductions is to slow the spread of the coronavirus. We calibrate the model, including public policies, to developments in Ontario in spring 2020. The model fits the epidemiological data quite well, including the second wave starting in late 2020. We find that socioeconomic interventions work well in the short term, resulting in a rapid drop off in new cases. The long run, however, is governed chiefly by health developments. Welfare cost calculations point to synergies between the health and socioeconomic measures.

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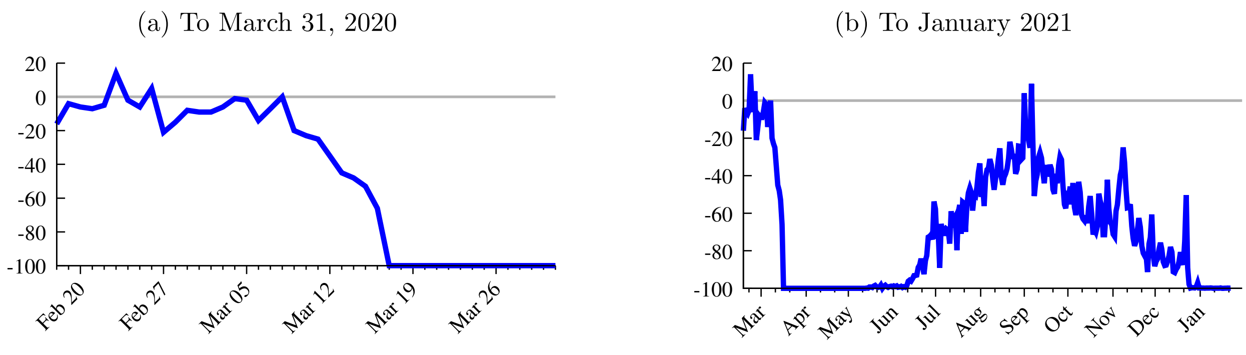
1 Introduction

The COVID-19 pandemic has severely disrupted social and economic activity around the world. Policymakers have responded to this once-in-a-lifetime event in myriad ways, ranging from border closures, travel bans, and lockdowns, to more-or-less business as usual. Confronted with this new threat, individuals responded rationally by reducing both their social contacts and a wide range of economic activity. By way of example, as shown in Fig. 1(a), restaurant reservations in Ontario made through the Open Table website fell off more than a week before the declaration of a state of emergency on March 17, 2020. Similarly, Fig. 1(b) reveals that Ontario restaurant reservations were falling throughout the autumn, as COVID-19 cases were rising. As individuals respond to the coronavirus menace, their collective actions affect the spread of the disease.

Figure 1: Open Table Reservations for Ontario



Note: Percentage change relative to previous year.

In this paper, we develop a model of the complex interactions between the epidemiology that describes the evolution of the coronavirus/COVID-19, and the social and economic choices of individuals. The textbook SIR (susceptible-infectious-recovered) epidemiological model is extended, first, by introducing additional states to account for the transmission of the coronavirus by asymptomatic individuals, and second, by modeling how socioeconomic choices of individuals influence the likelihood that they contract COVID-19. There are two key features on the socioeconomic side of the model. The first is a taste for social activity which contributes to the number of an individual's contacts, a factor that is relevant in determining the likelihood of catching the coronavirus. The second is a "fear of death" associated with catching the coronavirus. This fear of death introduces a wedge into the first-order conditions determining the choice of social activity, and hours of work. Consequently, in response to the pandemic, individuals endogenously choose to reduce their social activity (which is consistent with the restaurant reservation data in Fig. 1) as well as their work time.

In the model, policymakers can implement a variety of measures to curb the progression of the coronavirus. The public health policies are: measures to check contagion, like social distancing and mask mandates, hand sanitation in public places; and increased diagnostic testing, broadly construed to include not only actual testing, but also steps like contact tracing. The role of testing is to identify those who are COVID-19 positive so that they can self-isolate, thereby removing them from transmitting the disease. The socioeconomic policies are: restrictions on social activity, and business closures.

The model is calibrated to match epidemiological and economic developments in the province of Ontario in the spring of 2020; part of this calibration involves mapping public policy interventions into the available data. The rapid evolution on the epidemiological front implies that a model period should be short; it is set to a day. We then evaluate separately the health and socioeconomic protocols. Both help contain the spread of COVID-19. While the socioeconomic policies result in direct social and economic costs, they are also quite effective in the short term in reducing disease spread. Health interventions are more important for the longer term and come along with no apparent welfare cost. In other words, these sets of policies are complements, not substitutes.

Since March 2020, the literature on COVID-19 and its economic effects has exploded. What follows is a brief and selective survey of that literature, with emphasis on methodology and data that directly pertain to our work. Atkeson (2020) and Stock (2020) provide early overviews of the SIR framework, originated from Kermack and McKendrick (1927), in the context of the COVID-19 epidemic. The epidemiological side of our model augments Casares and Khan (2020) by introducing a time-varying contagion probability and the endogenous determination of interpersonal contacts, as well as the role for testing and isolating individuals. Examples of early work integrating economic modeling with epidemiological models are those on HIV by Kremer (1996), Philipson (2000), Gersovitz and Hammer (2004), Perrings et al. (2014), and Adda (2016). More recent and related contributions that connect macroeconomic models with household decision making and SIR models include Eichenbaum et al. (2020), Alvarez et al. (2020), Jones et al. (2020), Acemoglu et al. (2020), and Farboodi et al. (2020). A common theme in these papers is to clarify the trade-offs faced by policymakers, and to determine optimal public interventions in the presence of externalities in individual decision making. Eichenbaum et al. (2020) determine the speed and intensity of the optimal lockdown under various scenarios. Jones et al. (2020) discuss the externalities associated with infection and health-care congestion. Alvarez et al. (2020) discuss the timing, early versus late, of implementing public health measures in response to COVID-19 contagion. Farboodi et al. (2020) characterize the effects of equilibrium versus optimal social distancing. Acemoglu et al. (2020) consider different age groups in the SIR model and show that a strict and long lockdown for the most vulnerable group not only reduces infections, but allows for looser lockdowns for the lower-risk groups. Relatedly, Bodenstein et al. (2020) present a multi-sector model to capture the features of the U.S. Input-Output Tables and study how a shift towards tasks in non-core industries and remote work conditions can reduce the costs of social distancing in terms of output, consumption, and investment. In Diez de los Rios (2020), agents can substitute between market and home activity, thereby reducing their chance of infection. When agents are not fully rational, he finds that the effects of the pandemic are more severe than when agents are rational.

Another branch of the recent literature takes a more granular modeling approach to study the effects of COVID-19 contagion. Baqaee et al. (2020) evaluate reopening scenarios through both a sector- and activity-based contact matrix which is central to the evolution of contagion. Aguirregabiria et al. (2020) integrate the SIR model with a structural game of network production and social interactions. In their model, aggregate conditions, the presence in a particular social/production group and their location affect individual decisions. This interaction results in a tradeoff between productive/positive complementarities and infection. They estimate the model using Ontario data, and study the relative health and economic impacts of public policies. In contrast to these approaches which explicitly model the enormous heterogeneity associated with transmission, our model captures some key elements of these more granular approaches which permits the tractability afforded by our SIR-Socioeconomic model.

The rest of the paper is organized as follows. Section 2 presents the SIR-Socioeconomic model. Section 3 discusses the calibration of model parameters. Section 4 provides the quantitative analysis of pandemic scenarios and economic consequences over the first wave. Section 5 looks at the second wave which started late in 2020, and implications of a second lockdown. Section 6 concludes.

2 The SIR-Socioeconomic model

An important aspect of the model are the interactions between the epidemiological and socioeconomic sides of the model. In particular, public policy actions arising from epidemiological considerations – including mandates that influence the likelihood of being infected by the coronavirus, testing, and business shutdowns – affect the socioeconomic side of the model. Similarly, choices of work time, consumption and social activity arising on the socioeconomic side of the model shape disease dynamics on the epidemiological side.

2.1 The epidemiological side

In the textbook SIR model of Kermack and McKendrick (1927), an individual progresses from susceptible to infected, and thence from infected to either recovered or death. To capture key aspects of the novel coronavirus, we modify the basic SIR model, building on the discrete-time SIR model of Casares and Khan (2020). First, the incubation phase now captures the observation that there is an initial period in which an infected individual is infectious but asymptomatic. Second, since many of those who are post-incubation continue to be asymptomatic, we also include this distinction. Third, the term "recovered" is reserved for COVID survivors; the rest are dead, a distinction that proves important in the socioeconomic side of the model. Fourth, individuals are randomly tested. Consequently, infected but asymptomatic individuals may learn that they are COVID-positive, and so self-isolate, as do those who are symptomatic.[1] As shown below, the known versus unknown COVID status introduces interesting considerations regarding individual behavior.

To track the number of individuals by disease status, let s superscripts indicate those who are susceptible, i those who are infected, r the recovered, and d those who are dead. Further, k superscripts indicate that an individual knows their COVID status while x is used for those who do not know. The population size is fixed at N, and is divided into the following mutually exclusive groups as follows:

$$N_t^s + N_t^{ik} + N_t^{ix} + N_t^{rk} + N_t^{rx} + N_t^d = N. \tag{1}$$

Two important considerations from the socioeconomic side of the model now come into play. First, owing to business lockdowns, a fraction b_t of the labor force will be employed, leaving the rest unemployed. Second, conditional upon employment status, all those who know that they recovered from a COVID infection make the same decisions, resulting in the number of contacts y_t^{ek} and y_t^{uk} for the employed and unemployed, respectively. Similarly, y_t^{ex} and y_t^{ux} denotes socioeconomic contacts by those who are either susceptible or do not know their COVID status.

Since only those active cases who are unknown can transmit the virus (known cases self-isolate), taking their average number of contacts, the probability of encountering a COVID-

[1] To date, there has been very little testing to determine whether individuals have unknowingly had COVID. For this reason, this sort of seroprevalence testing is omitted from the model.

positive individual is

$$p_t = \frac{\left[b_t y_t^{ex} + (1-b_t) y_t^{ux}\right] N_{t-1}^{ix}}{\left[b_t y_t^{ex} + (1-b_t) y_t^{ux}\right] \left(N_{t-1}^{s} + N_{t-1}^{ix} + N_{t-1}^{rx}\right) + \left[b_t y_t^{ek} + (1-b_t) y_t^{uk}\right] N_{t-1}^{rk}}. \tag{2}$$

Notice that this probability depends not only on the size of the relevant populations, but also on their socioeconomic activity.

The number of new (actual) cases at time t is now given by

$$N_t^n = \alpha_t p_t \left[b_t y_t^{ex} + (1-b_t) y_t^{ux}\right] N_{t-1}^s. \tag{3}$$

In (3), α_t is the contagion probability in a single socioeconomic encounter, p_t is the probability that the encounter is with someone who is COVID positive, the term in square brackets is the average number of socioeconomic contacts by those who are susceptible, and their population size is N_{t-1}^s. The number of susceptibles at the end of the current period is, then,

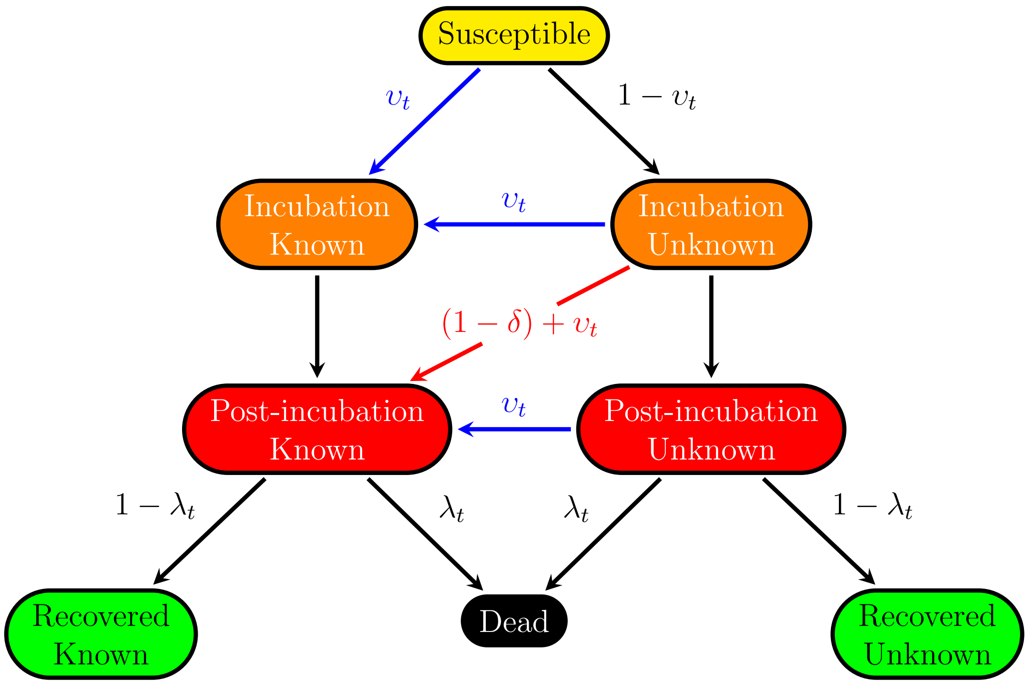
$$N_t^s = N_{t-1}^s - N_t^n. \tag{4}$$

Once infected, an individual passes through an incubation period lasting T_i days. This is followed by a post-incubation period lasting a maximum of T_p days. During the post-incubation period, a fraction $1/T_p$ of those who were new cases either die (with probability λ_t), or recover (with probability $1 - \lambda_t$). The average number of days spent in the post-incubation period is, then, $(T_p + 1)/2$, and the average number of days infected is $T_s = T_i + (T_p + 1)/2$.

The distinction between known and unknown COVID cases necessarily complicates the model. Fig. 2 summarizes the flows between various states. Start at the top with a susceptible individual.

Conditional upon infection, such an individual enters into the incubation period. Owing to testing, the individual may discover that they are COVID positive upon entering the incubation period; this occurs with probability υ_t; otherwise, the individual's status is un-

Figure 2: SIR-Socioeconomic Model Flows



known.[2] Each subsequent day spent in incubation, the individual's status may be revealed with probability υ_t. Those who move to the post-incubation period knowing their COVID status retain that information. For those who do not know, there are two possibilities: either they discover their COVID status because they are symptomatic (probability $1 - \delta$), or they are not symptomatic but are tested (probability υ_t). Upon exiting the infected phase, the individual may die (with probability λ_t), or recover. Those who recover either after having symptoms or being tested know that they have had COVID, the rest do not. It is assumed that once recovered, an individual remains immune to COVID – at least over the relatively short horizons considered below.

At time t, the number of individuals who are infected but do not know their COVID status is

$$N_t^{ix} = \sum_{j=0}^{T_i - 1} (1 - \overline{\upsilon}_{t,j}) N_{t-j}^n + \delta \sum_{j=0}^{T_p - 1} (1 - \overline{\upsilon}_{t,j+T_i}) N_{t-j-T_i}^n \left(\frac{T_p - j - 1}{T_p} \right) \tag{5}$$

[2] If performed, a test is perfectly informative. We abstract from the possibility of false positives or false negatives.

where

$$1 - \overline{\upsilon}_{t,j} \equiv \prod_{k=0}^{j} (1 - \upsilon_{t-k}) \tag{6}$$

is the probability at time t that an individual who was infected j periods ago has not learned their COVID status due to testing. The first sum in (5) adds up those in the incubation phase, the second those in post-incubation outcome phase. For those in post-incubation, recall that a fraction δ are asymptomatic. The last bracketed term accounts for the removing of those who exit to either recovery or death.

Similarly, the size of the infected population with known COVID status is

$$N_t^{ik} = \sum_{j=0}^{T_i-1} \overline{\upsilon}_{t,j} N_{t-j}^n + \sum_{j=0}^{T_p-1} \left[1 - \delta(1 - \overline{\upsilon}_{t,j+T_i})\right] N_{t-j-T_i}^n \left(\frac{T_p - j - 1}{T_p}\right). \tag{7}$$

The interpretation of (7) is similar to that of (5) with the first term covering those in the incubation phase, the second those in post-incubation.

The number of total deaths evolves according to

$$N_t^d = N_{t-1}^d + \lambda_t \sum_{j=0}^{T_p-1} \frac{N_{t-j-T_i}^n}{T_p}. \tag{8}$$

Finally, the size of the accumulated recovered populations are

$$N_t^{rk} = N_{t-1}^{rk} + (1 - \lambda_t) \sum_{j=0}^{T_p-1} \left[1 - \delta(1 - \overline{\upsilon}_{t,j+T_i})\right] \frac{N_{t-j-T_i}^n}{T_p} \tag{9}$$

$$N_t^{rx} = N_{t-1}^{rx} + (1 - \lambda_t)\delta \sum_{j=0}^{T_p-1} (1 - \overline{\upsilon}_{t,j+T_i}) \frac{N_{t-j-T_i}^n}{T_p} \tag{10}$$

where it is once again necessary to distinguish between those who know they have experienced COVID, (9), and those who have not, (10)

To gauge the effectiveness of testing and self-isolation, we define a *quarantine factor* as the share of unknown infected individuals with respect to active cases at the beginning of the day

$$q_t = \frac{N_{t-1}^{ix}}{N_{t-1}^{ix} + N_{t-1}^{ik}} \tag{11}$$

where $q_t = 1$ indicates no quarantining, and $q_t = 0$ perfect quarantining.

2.2 The socioeconomic side

In the analysis to come, what matters is how the economic environment during COVID-19 differs from pre-COVID-19 times. With this in mind, we start by describing the environment in pre-COVID-19 days. During those times, there is "nothing" for the government to do in the sense that there is no global pandemic for the government to respond to.

Aggregate output is given by $N^{1-\phi}H_t^{\phi}$ where H_t is the aggregate labor input, and N represents a factor in fixed supply. The units of this fixed factor are chosen so that there is one unit per member of the initial population. Per capita output is, then, $A_t^{1-\phi}h_t^{\phi}$ where $h_t(\equiv H_t/(N - N_{t-1}^d))$ is per capita hours, and $A_t = N/(N - N_{t-1}^d)$. Given the competitively-determined real wage, firms' choice of labor satisfies $w_t = \phi A_t^{1-\phi}h_t^{\phi-1}$, and per capita profits are $\pi_t = (1-\phi)A_t^{1-\phi}h_t^{\phi}$.

The typical worker maximizes utility,

$$\sum_{t=0}^{\infty} \beta^t U(c_t, h_t, d_t, s_t) \tag{12}$$

subject to the budget constraint,

$$c_t \leq w_t h_t + \pi_t - T_t \tag{13}$$

where π_t represents distributed profit income from firms, and T_t is a COVID-19-specific lump-sum tax (it only comes into play during the pandemic). In (12), s_t captures social interactions while d_t represents a "fear of death", relevant only during the pandemic. Utility is assumed to be additively separable over consumption, c_t, hours worked, h_t, the fear of death, and social interactions:

$$U(c_t, h_t, d_t, s_t) = \frac{c_t^{1-\sigma}}{1-\sigma} - \psi_h \frac{h_t^{1+\gamma}}{1+\gamma} - \psi_d d_t - \psi_s (s_{\max} - s_t)^2.$$

In pre-COVID-19 times, the fear of death is zero ($d_t = 0$) which helps motivate the fact that this variable enters preferences linearly; and the choice of social interactions will be $s_t = s_{\max}$ owing to the quadratic specification over contacts. Pre-COVID-19, the household chooses c_t, h_t and s_t to maximize (12) subject to (13) with $d_t = 0$.

Turn now to pandemic times when the government health authorities intervene in a number of ways. First, let τ be the fraction of telework performed in the economy in normal times. During COVID-19, the government increases the share of telework to $\tau' > \tau$ reflecting a move to work-at-home arrangements arising from orders to stay at home.

Second, the government can reduce business activity, b_t. Pre-COVID-19, all businesses are open and b_t is normalized to equal one. During the pandemic, we assume that the government manages business shutdowns based on a seven day average of new COVID-19 cases, subject to a minimum, b_{min}, corresponding to essential businesses and services, as well as telework jobs. Specifically,

$$b_t = \max\left\{b_{\min}, 1 - \frac{\eta}{7}\sum_{j=1}^{7}\frac{N^n_{t-j}}{N}\right\} \tag{14}$$

where η reflects the desire to flatten the epidemiological curves. The function (14) captures the fact that Ontario implemented a color-coded tier system for restrictions on socioeconomic activity, with differences across regions within Ontario.[3]

Third, government can restrict individuals' social activity, imposing the constraint

$$s_t \leq s_{\min}. \tag{15}$$

Finally, the government will require that all of those either having typical symptoms or testing positive for COVID-19 self-isolate, removing themselves from the labor market.

For firms, the move to more telework is of no consequence – it does not matter whether these jobs are performed in a traditional environment, or at home. Restrictions on business activity are more important, resulting in businesses temporarily shutting down. When this

[3]One might object to the business index depending on *actual* cases while the data contains only reported cases. If reported cases are a roughly constant fraction of actual cases, this apparent discrepancy amounts to changing the value of η in (14).

occurs, workers become unemployed.

The "fear of death" variable, d_t, is in play during the pandemic. We assume that, each day, an individual cares about the likelihood of dying:

$$d_t = \lambda_t \alpha_t y_t p_t. \tag{16}$$

There are two motivations for this particular specification of the variable d_t. First, suppose that dying is associated with a large utility cost (proxied by the preference parameter ψ_d in (12)). This utility cost, and the likelihood of dying, λ_t, then affect the value of being infected. Forward looking susceptible individuals take into account both the value of being infected, and the factors from the epidemiological side of the model that influence the chance of becoming infected: the likelihood of encountering a COVID-positive individual, p_t; the contagion probability, α_t; and the number of daily socioeconomic contacts, y_t. The second motivation for the specification for d_t is behavioral: susceptible individuals simply fear dying during the pandemic, and worry about the aforementioned factors that influence the chance of contracting COVID and dying during the pandemic.

The number of daily contacts is assumed to be linear in social activity, s_t, consumption, c_t, and non-telework time, $(1-\tau_t)h_t$:

$$y_t = s_t + \mu_c c_t + \mu_h (1-\tau_t) h_t. \tag{17}$$

The parameters μ_c and μ_h allow for differential effects of consumption and work time on daily contacts relative to the count of social contacts.

During the pandemic, workers are no longer alike. Those who either develop symptoms or test positive for COVID-19 are required to self-isolate in quarantine and so are not in the labor force; from Section 2.1, this group numbers N_{t-1}^{ik}. Of those who remain alive, some are unemployed because the government has ordered the businesses they work for closed; the rest remain employed. Below, the superscript e denotes choices of the employed, u of the unemployed, and n of non-participants (the quarantined). Government provides an income supplement to all those who do not work equal to a fraction θ of pre-pandemic earnings, wh.

Our modeling of the fear of death and individuals' inability to save has two important implications : First, individuals solve a sequence of static problems; and second, among participants the key distinction is between those who know their COVID status and those who do not. From Section 2.1, the size of the first group is $N_{t-1}^{ik} + N_{t-1}^{rk}$ (infected and recovered, both with known COVID status) while the second is of size $N_{t-1}^{s} + N_{t-1}^{ix} + N_{t-1}^{rx}$ (susceptible, infected but do not know it, and recovered but do not know it). Individuals in this latter group do not know which subpopulation they belong to, and so will make the same decisions. Following the notation introduced in Section 2.1, k superscripts will denote decisions of those participants who know their COVID status, while x superscripts will index decisions by all others.

Given the discussion above, the problem of an employed agent with unknown COVID status is

$$\max_{\{c_t^{ex}, h_t^{ex}, s_t^{ex}\}} U(c_t^{ex}, h_t^{ex}, d_t^{ex}, s_t^{ex})$$

subject to

$$c_t^{ex} = w_t h_t^{ex} + \pi_t - T_t \tag{18}$$

where

$$d_t^{ex} = \lambda_t \alpha_t y_t^{ex} p_t \tag{19}$$

$$y_t^{ex} = s_t^{ex} + \mu_c c_t^{ex} + \mu_h (1 - \tau_t) h_t^{ex}. \tag{20}$$

Recall from (2) that p_t is the probability of encountering an infected individual.

When workers are free to choose their social contacts, the resulting Euler equations are:

$$\begin{aligned} U_2(c_t^{ex}, h_t^{ex}, d_t^{ex}, s_t^{ex}) + w_t U_1(c_t^{ex}, h_t^{ex}, d_t^{ex}, s_t^{ex}) \\ + [w_t \mu_c + \mu_h(1 - \tau_t)] \lambda_t \alpha_t p_t U_3(c_t^{ex}, h_t^{ex}, d_t^{ex}, s_t^{ex}) = 0 \end{aligned} \tag{21}$$

$$\lambda_t \alpha_t p_t U_3(c_t^{ex}, h_t^{ex}, d_t^{ex}, s_t^{ex}) + U_4(c_t^{ex}, h_t^{ex}, d_t^{ex}, s_t^{ex}) = 0 \tag{22}$$

Contrast these conditions with the corresponding pre-pandemic conditions,

$$U_2(c_t^e, h_t^e, d_t^e, s_t^e) + w_t U_1(c_t^e, h_t^e, d_t^e, s_t^e) = 0 \tag{23}$$

$$s_t = s_{\max}. \tag{24}$$

Since U_3 is the disutility from being at risk of dying from COVID, comparing (22) with (24) shows that the first term in (22) represents a wedge in the choice of socioeconomic contacts and that during the pandemic, individuals *choose* fewer such contacts. Comparing (21) and (23) similarly reveals a pandemic-induced wedge in individuals' choice of hours worked: since consumption is associated with more contacts, the fear of death both reduces the net marginal benefit of consuming; and by the same token, the fear of death increases the marginal cost of working.[4]

Those who are employed with known COVID status have no fear of death due to the immunity conferred by virtue of being recovered. Consequently, their problem is the same as in the pre-pandemic period and the solutions to their problems are governed by (23) and (24).

Turn next to those with unknown COVID status who are unemployed. Since they have no work decision, they solve:

$$\max_{\{c_t^{ux}, s_t^{ux}\}} U(c_t^{ux}, 0, d_t^{ux}, s_t^{ux})$$

subject to

$$c_t^{ux} = \theta w h + \pi_t - T_t \tag{25}$$

where

$$d_t^{ux} = \lambda_t \alpha_t y_t^{ux} p_t \tag{26}$$

$$y_t^{ux} = s_t^{ux} + \mu_c c_t^{ux}. \tag{27}$$

[4]There will be a general equilibrium effect: lower employment during the pandemic will push up the equilibrium real wage. Absent such an increase, both consumption and hours worked decline.

Recall that those who are not employed receive from government a fraction θ of pre-pandemic earnings, and consumption is determined by the budget constraint. When individuals are unconstrained in their choice of socioeconomic contacts, the resulting Euler equation is

$$\lambda_t \alpha_t p_t U_3(c_t^{ux}, 0, d_t^{ux}, s_t^{ux}) + U_4(c_t^{ux}, 0, d_t^{ux}, s_t^{ux}) = 0$$

which, again, illustrates that the coronavirus will reduce the choice of social contacts, s_t^{ux}, as the probability of being infected rises.

The unemployed with known COVID status have no fear of death, and absent government constraints on socioeconomic activity will choose $s_t^{uk} = s_{\max}$ and their consumption is given by their budget constraint.

Non-participants have no choices; owing to the requirement of isolation, their socioeconomic contacts are at a minimum, $y_t^n = s_t^n = s_{\min}$, and their utility is

$$U(\theta wn + \pi_t - T_t, 0, d_t^n, s_{\min}).$$

The fear of death value for non-participants is $d_t^n = \lambda_t$ since non-participants are necessarily infected.

Aggregate consumption, hours, social activity, socioeconomic contacts and output are computed as:

$$C_t = (N_{t-1}^s + N_{t-1}^{ix} + N_{t-1}^{rx})\left[b_t c_t^{ex} + (1-b_t)c_t^{ux}\right] + N_{t-1}^r\left[b_t c_t^{ek} + (1-b_t)c_t^{uk}\right] + N_{t-1}^{ik} c_t^n \tag{28}$$

$$H_t = (N_{t-1}^s + N_{t-1}^{ix} + N_{t-1}^{rx}) b_t h_{t-1}^{ex} + N_{t-1}^{rk} b_t h_t^{ek} \tag{29}$$

$$S_t = (N_{t-1}^s + N_{t-1}^{ix} + N_{t-1}^{rx})\left[b_t s_t^{ex} + (1-b_t)s_t^{ux}\right] + N_{t-1}^r\left[b_t s_t^{ek} + (1-b_t)s_t^{uk}\right] + N_{t-1}^{ik} s_t^n \tag{30}$$

$$Y_t = (N_{t-1}^s + N_{t-1}^{ix} + N_{t-1}^{rx})\left[b_t y_t^{ex} + (1-b_t)y_t^{ux}\right] + N_{t-1}^r\left[b_t y_t^{ek} + (1-b_t)u_t^{uk}\right] + N_{t-1}^{ik} y_t^n \tag{31}$$

$$\mathrm{GDP}_t = N^{1-\phi} H_t^{\phi}. \tag{32}$$

The corresponding per capita variables are computed by dividing through by the still-living population, $N - N^d_{t-1}$.

The COVID-19-specific portion of the government budget constraint is

$$\theta wn[(1-b_t)(N^s_{t-1} + N^{ix}_{t-1} + N^{rx}_{t-1} + N^{rk}_{t-1}) + N^{ik}_{t-1}] = T_t(N - N^d_{t-1}) \tag{33}$$

That is, the government levies a lump-sum tax, T_t, on all living workers in order to finance payments to the unemployed and non-participants. This setup is equivalent to one in which Ricardian government debt is used to balance the government budget.

To evaluate the trade-offs associated with restricting socioeconomic activity in the model, we compute the usual Hicksian equivalent variant payment. Each day t, the welfare cost of the pandemic is measured by the value of ξ_t satisfying

$$\begin{aligned}(N - N^d_{t-1})U\left((1-\xi_t)c, h, 0, s_{\max}\right) \\ &= (N^s_{t-1} + N^{ix}_{t-1} + N^{rx}_{t-1})\left[b_t U(c^{ex}_t, h^{ex}_t, d^{ex}_t, s^{ex}_t) + (1-b_t)U(c^{ux}_t, h^{ux}_t, d^{ux}_t, s^{ux}_t)\right] \\ &\quad + N^{ik}_{t-1}U(c^n_t, 0, d^n_t, s_{\min}) \\ &\quad + N^{rk}_{t-1}\left[b_t U(c^{ek}_t, h^{ek}_t, d^{ek}_t, s^{ek}_t) + (1-b_t)U(c^{uk}_t, h^{uk}_t, d^{uk}_t, s^{uk}_t)\right]\end{aligned} \tag{34}$$

where c and h are pre-pandemic consumption and hours. That is, each day, ξ_t measures the fraction of pre-pandemic consumption that could be taken away and leave the worker as well off as receiving average utility during the pandemic. The use of average utility during the pandemic can be justified by invoking the Rawlsian veil of ignorance. The idea is that workers are asked about how they feel about the pandemic prior to finding out what their status will be during those times.

3 Calibration

The model is calibrated using a combination of data for the Canadian province of Ontario, and previous studies covering both economics and epidemiology. The baseline calibration is summarized in Table 1.

The initial (pre-pandemic) population, N, is set to 14.66 million which corresponds to Ontario's population at the end of 2019 as reported by Ontario Economic Accounts (2020)

Turn now to the epidemiological parameters. The initial value of the probability of contagion in a single contact, α, was chosen so that the baseline model roughly matches both the peak and cumulative deaths over the first wave in Ontario. The resulting value is $\alpha = 0.0205$. Based on epidemiological evidence reported by Anderson et al. (2020), the length of the incubation period is $T_i = 5$ days, and the average duration of the disease is $T_s = 16$ days. These values imply that individuals are in the post-incubation phase for a maximum of $T_p = 21$ days.

There is considerable uncertainty regarding the infection fatality rate. Public Health Ontario (2020) estimated a case fatality rate of 2.8% for May 2020. However, as an estimate of the infection fatality rate, the case fatality rate is likely too high since it is based on reported COVID-19 cases, and so omits asymptomatic. Early in the pandemic (February 2020), the World Health Organization (2020a) reported rates between 0.3 and 1%. More recently, Verity et al. (2020) estimated an overall case fatality rate of 0.66% for China. For the baseline calibration, we set initially $\lambda = 0.8\%$ as a middle ground between the very high case fatality rate from Public Health Ontario, and the lower rates from the World Health Organization. As the virus spreads and there are public health interventions, the treatments improve and the prevalence of the age-group contagion swings from more vulnerable to less vulnerable groups. Following Levin et al. (2020), assume a downwards trend for λ to capture this decline in the infection fatality rate.

Next, what fraction of COVID-19 cases are asymptomatic? According to the World Health Organization (2020b), "80% of infections are mild or asymptomatic, 15% are severe infection, requiring oxygen and 5% are critical infections, requiring ventilation". Oran and Topol (2020) provide a narrative review based on data from 16 cohorts (snapshots at various points in time in different locations). They state: "Asymptomatic persons seem to account for approximately 40% to 45% of SARS-CoV-2 infections, and they can transmit the virus to others for an extended period, perhaps longer than 14 days." Their finding is consistent with the best estimate of the CDC (2020) that 40% of infections are asymptomatic. On this basis, we set $\delta = 0.4$. The diagnostic testing rate is initially set at $\upsilon = 0$ to reflect the lack of testing early in the pandemic.

On the socioeconomic side of the model, the weight on the disutility of labor, ψ_h, is chosen so that in the pre-pandemic steady state, hours are $h = 1$. The coefficient of relative risk aversion, σ, is set to 1.5 which is well within the range typically employed in macroeconomics. Microeconomic evidence (for example, Altonji 1986) points to a low Frisch labor supply elasticity. Setting $\gamma = 4$ implies an elasticity of $1/4$. The elasticity of output with respect to labor, ϕ, is set to 0.75; this value implies that 25% of income is received as profits.

Recall that daily contacts, y_t, depends linearly on social contacts as well as economic activity (consumption and hours worked). Due to telework, only a fraction $(1 - \tau) = 0.87$ of pre-pandemic hours worked result in daily contacts; see Deng et al. (2020). Given the parameter value on hours, $\mu_h = 6$, there are 5.22 daily contacts due to work. Since pre-pandemic consumption is also 1, setting $\mu_c = 2$ means that there are 2 daily contacts due to consumption. Social contacts range from a low of $s_{\min} = 2$ (a binding constraint during the lockdown which reflects in-home contacts that cannot be avoided) to a maximum daily value of $s_{\max} = 8$ which characterizes social life in normal, pre-pandemic times.[5]

Evidence on the value of a statistical life is used to calibrate ψ_d, the "fear of death" utility parameter. Kaplan et al. (2020), citing Lavetti (2020), used a value of a statistical life of US$4 million, or $5.2 million (Canadian dollars, using an exchange rate of 1.3). These values are close to the median value of just over $4 million reported by Bellavancea et al. (2009). We need to express the value of a statistical life in units of utility. Conceptually,

[5] The average household size in Ontario is 2.56 (https://www.fin.gov.on.ca/en/economy/demographics/census/cenhi16-5.html). We introduced the minimum level of social contacts, $s_{\min}$, to capture the stay-at-home enforcement of a severe lockdown. If we take $2.56 - 1 = 1.56$ home-related contacts as a reference value for an individual, setting $s_{\min} = 2$ leaves 0.44 daily contacts to account for a range of other, non-household contacts.

this is obtained as

$$\psi_d = \frac{\text{Value of a statistical life}}{\text{Daily per capita consumption}} \times \text{Model consumption} \times \begin{array}{c}\text{Marginal utility}\\ \text{of consumption}\end{array}.$$

That is, start by expressing the value of a life relative to daily consumption, convert the units to conform to consumption units in the model, c, then finally convert into utility units by multiplying by the marginal utility of consumption, $c^{-\sigma}$. For 2019, Ontario Economic Accounts (2020) gives total consumption for Ontario of \$718.316 billion, and a population of 14.66 million, so daily per capita consumption is \$134.25. Pre-pandemic consumption is 1 as is the marginal utility of consumption. Thus, $\psi_d = 38,737$.

Similarly, evidence on the utility value of reduced social contacts is used to calibrate the value of ψ_s, the taste for social activity. Specifically, ψ_s is obtained from

$$\psi_s(s_{\max} - s_{\min})^2 = \begin{array}{c}\text{Value of social contacts}\\ \text{(\% of income)}\end{array} \div \frac{\text{Consumption}}{\text{Income}} \times c \times \begin{array}{c}\text{Marginal utility}\\ \text{of consumption}\end{array}.$$

Based on a Swedish survey administered in mid-April 2020, Andersson et al. (2020) estimate that the welfare cost of a month-long stay-at-home policy is 9.1% of (monthly) income. Assuming that Swedes and Ontarians are sufficiently similar that Ontarians would similarly experience a 9.1% of income loss during a lockdown, this loss can be expressed relative to consumption by dividing by the consumption-income ratio, 0.794 (based on figures for the last quarter of 2019 as reported in (Ontario Economic Accounts 2020)). Again, pre-pandemic consumption in the model is 1 as is its marginal utility. Finally, since the lockdown reduces social contacts from $s_{\max} = 8$ to $s_{\min} = 2$, $\psi_s = 0.00318$.

There are two parameters in the policy function (14) governing business activity: $b_{\min}$, the minimum for business activity; and η which governs the feedback between new COVID-19 cases and business activity. The value of $b_{\min}$ is determined by: (1) the fraction of essential jobs in Ontario, 40%;[6] and (2) the fraction of jobs in Ontario that can be performed at home,

[6] Sectors delivering essential goods and services are: (i) Occupations in front-line public protection services, (ii) Healthcare and social assistance, (iii) Forestry/fishing/mining/quarrying/oil/gas, (iv) Construction, (v) Agriculture, (vi) Manufacturing, (vii) Transportation and warehousing, (viii) Finance and insurance, and (ix) Occupations in law and social, and community and government services. The data are from Haver

41.7% according to Deng et al. (2020), the highest proportion among Canadian provinces. Thus, $b_{\min} = .4 + (1 - .4) \times .417 \simeq 0.65$. The feedback parameter, η, was chosen so the policy function (14) implies an average job destruction during the lockdown period similar to that experienced by the Ontario labor market. According to Labour Force Survey (2020), Ontario's employment decreased by 10.3% (788,600 jobs) between February and June 2020.[7] Setting $\eta = 480$ delivers an average reduction in employment of 10.3% over the lockdown period which roughly corresponds to the second quarter of 2020.

Finally, labor income of the non-employed is set to a fraction $\theta = 0.52$ of pre-pandemic labor earnings. This value was obtained by dividing the Canada Emergency Response Benefit of \$2,000 per month by per capita labor income for Ontario (75% of monthly per capita income in Ontario \$61,716/12, based on the final quarter of 2019).

4 Simulation Results

This section presents model simulations for a baseline policy corresponding, roughly, to the actual policies of the Ontario government, as well as alternative scenarios geared to understanding which elements of Ontario's COVID response were most important. Here, we focus on the first 365 days (one year) starting from the arrival of the first infected individual in Ontario.

For all scenarios, it is assumed that during the lockdown period, the infection fatality rate falls linearly from its benchmark value of 0.8% to 0.3% as shown in Fig. 3(b). This decline reflects improvements in best practices for the treatment of COVID patients, and actions taken to limit spread of the coronavirus to vulnerable populations, like the elderly (see Levin et al. 2020).

For all scenarios, starting on the first day of the lockdown, we assume that all jobs that

(Table 14-10-0355) and CANSIM Table 14-10-0296-01.

[7] In particular, Ontario Employment Report (2020) states that "Over the February-May period, Ontario employment declined by almost 1.2 million, the largest three-month employment decline on record. With this increase, Ontario employment in June was 778,600 (10.3%) lower than the February level." See https://www.ontario.ca/page/labour-market-report-june-2020

Table 1: Numerical values of model parameters

Population, people	$N = 14.66$ million
Initial contagion probability	$\alpha = 0.0205$
Incubation period, days	$T_i = 5$
Average disease duration, days	$T_s = 16$
Fatality rate	$\lambda = 0.008$
Asymptomatic cases rate	$\delta = 0.4$
Consumption marginal contacts	$\mu_c = 2$
Labor marginal contacts	$\mu_h = 6$
Telework share	$\tau = 0.13$
Minimum social contacts	$s_{\min} = 2$
Maximum social contacts	$s_{\max} = 8$
Elasticity of consumption marginal utility	$\sigma = 1.5$
Elasticity of labor marginal disutility	$\gamma = 4$
Weight of labor disutility	$\psi_h = 0.75$
Weight of contagion disutility	$\psi_d = 38,737$
Weight of social contacts utility	$\psi_s = 0.00318$
Labor elasticity in production technology	$\phi = 0.75$
Business shutdown feedback parameter	$\eta = 480$
Minimum business activity	$b_{\min} = 0.65$
Unemployment subsidy coefficient	$\theta = 0.52$

can be done at home are, in fact, performed at home and so set $\tau = 0.417$, based on evidence from Deng et al. (2020) discussed above.

4.1 Baseline

The first task is to establish the timing of key events for the model. January 25, 2020 marks day 1 when the first COVID patient tested positive in Ontario. The disease initially spread slowly in Ontario. It was not until March 17 (day 53) that Premier Doug Ford declared a state of emergency. The actual interventions started on March 24 (day 60) when Premier Ford signed an order to enforce social distancing and shutting down all non-essential businesses. In terms of the model, these interventions imply that on day 60,

1. Social contacts are set to $s_{\min}$, reflecting the effects of the order to restrict social contacts to those required for basic needs, and the strong recommendation to stay at home.

2. Business activity is given by (14) instead of its pre-pandemic normalized value of $b = 1$.

3. The contagion probability, α_t, dips by 25%. This change captures the effects of various required preventative measures such as wearing face masks, increased hand washing, and the use of disinfectants.

4. The rate of diagnostic testing for COVID is set to $\upsilon_t = 3.5\%$, reflecting our best guess as to this testing rate. As a point of fact, testing rose rapidly from $1,842$ in March to $7,321$ in April to $14,219$ in May. Since υ_t is the daily probability of detecting an asymptomatic case, the likelihood that a given asymptomatic agent is detected while infectious is closer to 50%.

The interventions 1 and 2 are referred to as the socioeconomic policies; the interventions 3 and 4 are the health policies.

The actions taken by the Ontario government were quite successful in containing the spread of the coronavirus. On June 12 (day 140), the province initiated a gradual reopening of socioeconomic activity. Some restrictions remained in place, and regions within the province moved to different phases of reopening depending on their new and active case counts. To capture these effects in the model, starting on day 140,

1. Individuals are permitted to choose the number of social contacts, s_t.

2. The business shutdown feedback parameter, η, is revised to reflect the reduction in the infection fatality rate over the lockdown. Specifically, the value of η is decreased by the ratio of the pre-lockdown fatality rate to its value at the end of the lockdown, 0.3%/0.8%.

3. Motivated by observed patterns in seasonal cold and flu, we assume that the contagion probability diminishes over the summer by an additional 25% (as activities move outdoors), then rises again in the autumn (when activities move back indoors, and students return to school) as shown in Fig. 3(a).

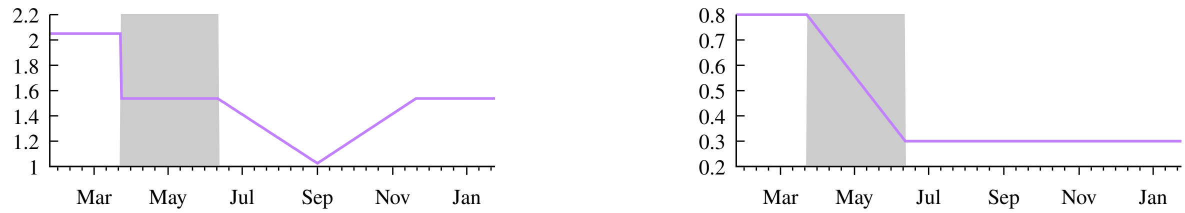
4. The testing probability, υ_t, remains at 3.5%.

Given the timing of interventions described above, the first year over which the model is simulated has four broad phases: pre-intervention between January 25 and March 23 (days 1 and 59); the lockdown lasting from March 24 through June 11 (days 60 to 139); the (gradual) reopening starting on June 12 (day 140); and a second wave starting in November, eventually leading to a second lockdown starting December 26 (discussed in Section 5).

The model provides everyone's epidemiological status as known; the same cannot be said of the data due to the presence of asymptomatic cases as well as limited testing capacity. Arguably, the best measured data is for deaths. As a preliminary check on the model, the left two panels in Fig. 4 compare model's predictions for daily and total deaths with those reported for Ontario. While the model captures the general patterns seen in the data – in

Figure 3: Key driving processes

(a) Contagion probability (%), α_t (b) Fatality rate (%), λ_t



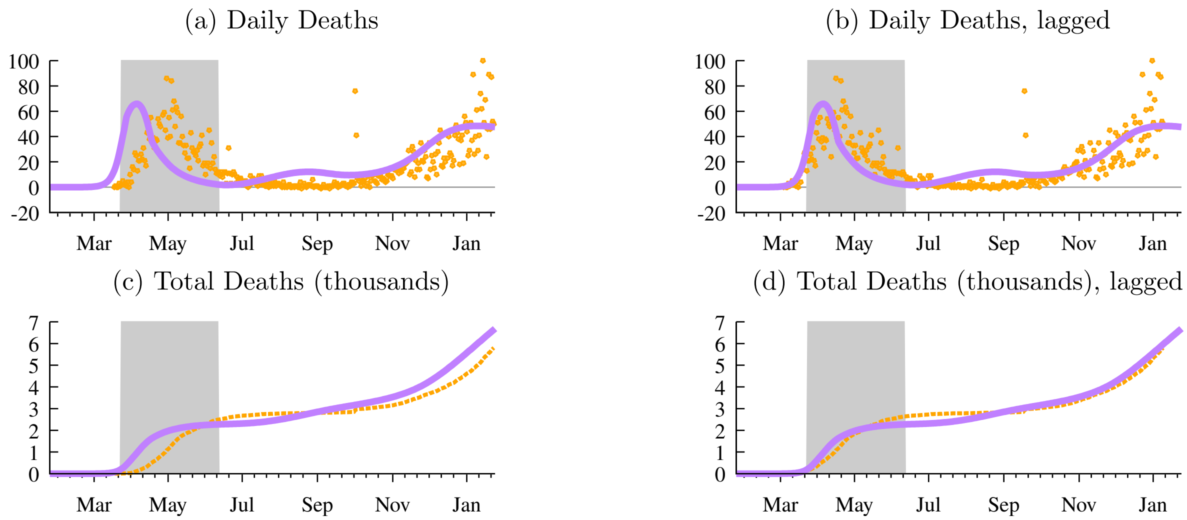
Legend: The shaded area marks Ontario's first lockdown.

particular, the rise and fall in daily deaths during the lockdown – the model's peak in daily deaths is too early relative to the data. There are at least two plausible explanations for this time gap between the model and the data. First, health authorities may have reported deaths with a lag, particularly early in the pandemic when procedures had not yet been put in place. Second, our model limits the maximum duration of the disease to 26 days (the incubation phase lasts $T_i = 5$ days while the maximum length of the post-incubation phase is $T_p = 21$ days); in fact, there are a small number of individuals whose infection is considerably longer, and who may end up dying. When the Ontario data is lagged by 14 days – as in the right panels of Fig. 4 – the model's fit improves. Of note is the model's prediction of a minor wave peaking in September, followed by a second wave starting in November, also reflected in the data.

The left hand panels of Fig. 5 summarize the epidemiological side of the model. The various restrictions associated with the lockdown – along with endogenous responses of agents in the model – bring about a drop in new cases. While new cases can fall quickly, the number of active cases declines more gradually due to the length of the infection period (on average, 16 days). More active cases ultimately leads to more daily deaths, which peak in late March. One year after the onset of the pandemic, the model predicts $6,592$ dead and over 2 million total cases (13.8% of the initial Ontario population) – far short of estimates for so-called "herd immunity".

On the economic side, the lockdown leads to an immediate plunge in employment of

Figure 4: Deaths: Baseline versus Ontario Data

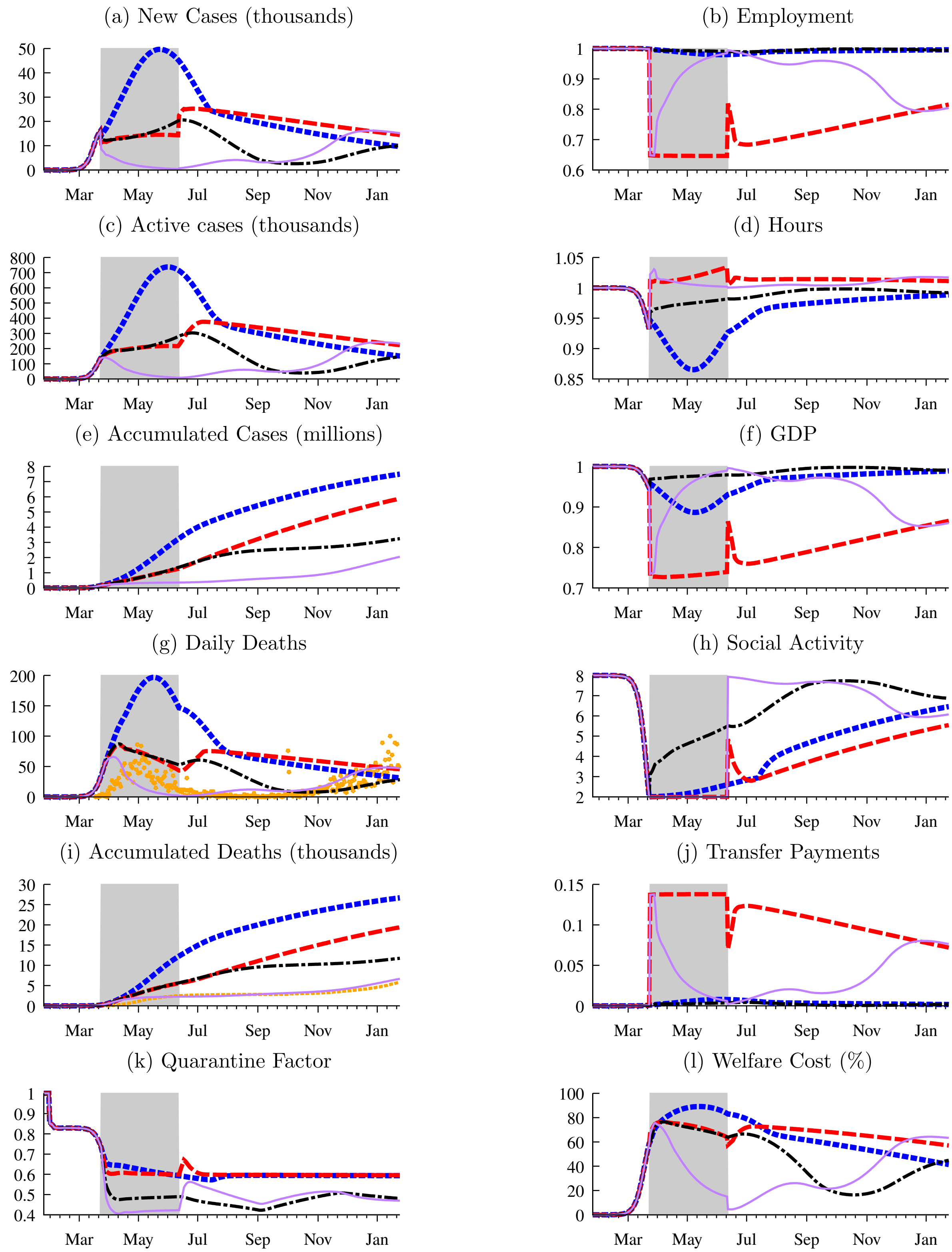


Legend: Baseline, solid purple; Ontario data, dotted orange. Shaded area: the lockdown. "Lagged" takes a 14 day lag of the Ontario data.

around 35%. However, a week into the lockdown, employment has recovered to 76% of its pre-pandemic level, and by mid-April stands at 87%. These employment losses are chiefly due to the policy function, (14), which specifies the fraction of open businesses as a function of a seven day average of new cases.

An interesting prediction of the model is that both hours worked and social activity start declining *prior* to the lockdown representing the endogenous response of agents to the growing number of active cases operating through the fear of death (recall Fig. 1 which shows that restaurant reservations in Ontario started falling before the state of emergency was declared in the spring). This predictions dovetails nicely with the restaurant reservation data for Ontario presented in Fig. 1. During the lockdown, social activity is restricted to its minimum value of two daily contacts. Once the lockdown is in place, average hours rise sharply and run above their pre-pandemic value of one. What is going on is that the reduction in employment boosts the marginal product of labor, and so the real wage; this increase in the real wage is sufficiently high to increase average hours, despite workers' fear of death. Owing to the downturn in average hours prior to the lockdown, output (GDP)

Figure 5: Baseline Policies.



Legend: Baseline, solid purple; no interventions, dotted blue; socioeconomic interventions only, dashed red; health interventions only, dot-dashed black; lockdown, the shaded area.

also declines. During the lockdown, output dynamics are largely determined by those of employment; output plunges precipitously at the outset, then partly recovers over the period of a few weeks. By the end of the lockdown, output is within a couple of percentage points of its pre-pandemic value.

Early in the pandemic, the employment losses lead to a surge in COVID-related transfer payments. Naturally, as employment recovers, these transfer payments drop.

Post-lockdown, recall that the contagion probability, α is assumed to decline over the summer before rising again in the autumn, as depicted in Fig. 3(a). In light of the fall in the infection fatality rate, the government lowers its setting for the parameter η which relates business closures to the number of new cases. Despite the favorable developments regarding the contagion probability, new cases start to rise again owing to an increase in socioeconomic contacts, leading to renewed business closures as reflected in the employment numbers. However, owing to the downward revision in the feedback parameter η, business closures are not as severe as under the lockdown. The increase in new cases eventually leads individuals to slightly reduce their social activity.

4.2 No Policy Response

How efficacious were the four policy interventions described at the start of Section 4.1? This question is answered by removing these interventions: the contagion probability, α remains 0.0205; testing, υ remains zero; individuals freely choose their social activity; and all businesses remain open. However, due to learning about treating COVID, the likelihood of dying from COVID, λ, declines as under the baseline.

The implication of this no-policy scenario are summarized by the blue dotted lines in Fig. 5. New cases continue to rise during what would have been the lockdown, peaking just shy of 50 thousand in late May. Active cases peak a bit later (early June) when over 737 thousand are infected. However, the plateau for daily deaths, 197, occurs earlier (mid-May) owing to the declining fatality rate.

Starting in mid-June, new cases start to decline, followed by active cases and deaths. What is going on is that by late June, nearly 4 million (27% of the population) either have COVID, or have recovered; under the baseline, the corresponding figure is 378 thousand. With such a large fraction of the population immune, herd immunity dynamics are starting to take effect and new cases start to fall. However, achieving herd immunity is an excruciatingly slow process. One year into the pandemic 7.5 million are immune (51% of the population), yet new cases are still running $9,725$ per day, and 32 people die from COVID each day.

With no business closures, the only reason for employment to deviate from 100% is due to self-isolation of those who develop symptoms in the post-incubation phase of the disease. Transfer payments are, consequently, low. The patterns for social activity and hours worked reflect the endogenous choices of individuals facing rising case numbers. Average hours worked decline through early May before starting to move up. Social activity plummets to its minimum of two, then starts to inch up. Nonetheless, socializing remains well below its pre-pandemic levels throughout that first year.

Deaths provide a measure of the effectiveness of the policy interventions. At the end of a year, the no-policy scenario predicts 26.6 thousand would be dead compared to $6,592$ under the baseline. This no-policy scenario no doubt understates fatalities since our modeling does not account for hospital constraints. As mentioned earlier, infections peak at around 735 thousand cases. Roughly 2/3 of these cases are post-incubation, or approximately 500 thousand. The U.S. Centers for Disease Control and Protection reports that 14% of cases required hospitalization, and 2% were admitted to ICU (intensive care units). Assuming that these U.S. figures are representative of what could be expected in Ontario, at the peak, 70 thousand require hospitalization, and 10 thousand need ICU. Both of these number far exceed Ontario's capacity.

Another measure of policy effectiveness is the quarantine factor, the fraction of infected individuals who do not know it and continue their socioeconomic activity. With no policies, this fraction declines over the lockdown from 70% to 60% compared to just over 40% for the baseline policies. Yet another measure of the balance between the epidemiological and socioeconomic restrictions is the welfare cost. Recall that this cost is measured relative to an idealized no-pandemic steady state. By this metric, no interventions are significantly costlier than the baseline policies as shown in Fig. 5: 56% versus 31% of consumption.

What accounts for the differences between the baseline and no-policy scenarios: the health interventions, or the socioeconomic restriction? The next two subsections answer this question.

4.3 Health Policies Only

These are comprised of the decrease in the contagion probability, α, and an increase in testing, υ. The effects of these interventions are summarized by the black dot-dashed lines in Fig. 5.

Since the proximate effects of health interventions are on the epidemiological side of the model, we start there. Upon implementation on March 24, the model predicts a slight decline in new cases. However, social contacts increase (they are unconstrained under this scenario), and new cases continue to rise until June 12 when the assumed summer decline of the contagion rate starts. Active cases follow a dynamic similar to that seen for new cases. That daily deaths start to decline in early April can be attributed to the assumed decrease in the COVID death rate, λ. In summary, it is not the start of the "seasonal" fall in contagion that the coronavirus situation is brought under control. Yet, starting in November, new cases are rising and a nascent second wave is in the offing.

Since the health policies do not prescribe business closures, employment is only slightly below its pre-pandemic level, and pandemic-related transfers are negligible. However, average hours worked remains well below that seen in the baseline scenario, as does post-lockdown social activity – although both hours and social activity are well above the levels predicted under the no-policy scenario. With only health policies in place, the fall in GDP is 1/5 of that seen under the baseline policies. Nonetheless, the welfare cost of the pandemic is 9 percentage points higher than the baseline (40.5% compared to 31.3%): the positive effects of relatively higher consumption, fewer hours, and more social activity are offset by the disutility associated with the fear of death arising from the much greater prevalence of the coronavirus.

At the end of the first year, the health interventions see 11.7 thousand dead compared to $6,592$ under the baseline. Compared to the baseline, the health-only measures are less effective in quarantining COVID cases during the lockdown, and more effective after.

4.4 Socioeconomic Policies Only

The red dashed lines in Fig. 5 summarize the model's predictions for a case in which the only interventions of the Ontario government are closing businesses according to the feedback rule (14), and restricting social activity to an absolute minimum ($s_{min} = 2$) over the lockdown period.

At the start of the lockdown, business closures are quite similar to that seen under the baseline. However, absent the baseline's health interventions, new cases run higher through the lockdown. The business closure feedback rule, (14), then implies that more businesses remain closed. Employment is, consequently, lower than the baseline, and transfer payments higher.

Focus, for the moment, on the disease progression during the lockdown. Over this period, the socioeconomic interventions are more effective in containing the number of new cases than the health interventions alone, but less effective than both sets of interventions (the baseline). At the end of the lockdown, active cases, daily deaths and total deaths are lower under the socioeconomic interventions than the health interventions.

This picture changes in the months immediately after the lockdown during which the health interventions result in better epidemiological results than the socioeconomic interventions. These differences can be attributed to a combination of factors. First, on the socioeconomic side, the downward adjustment of η, the feedback parameter in the business closure function (14), results in a temporary increase in open businesses immediately after the lockdown. This respite is, however, short lived. Similarly, after the lockdown, individuals are free to choose their social activities, resulting in a transitory increase in social activity. As a result of these increases in business and social activity, new cases rise sharply after the lockdown. Despite the subsequent business closures and decline in social activity, new cases remains high, and ultimately so do deaths.

Second, as discussed above, the health interventions are a combination of testing and contagion-reduction measures. Absent both of these interventions, there is little to check the progress of the disease apart from the endogenous response of individuals (choosing to consume less, work fewer hours and reduce their social contacts), and the business closure rule. Evidently, these mechanisms are insufficient to control the spread of the coronavirus. These results reinforce the message that public health measures are key to the long run containment of the coronavirus.

At the end of the first year of the pandemic, daily deaths under the socioeconomic interventions are higher than the no-intervention case (46 compared to 32). That total deaths are lower (19.3 thousand versus 26.6 thousand) is due to the lower fatalities during and shortly after the lockdown period. The prospects for the second year of the pandemic are dim.

4.5 Discussion and alternative parameterizations

Table 2 summarizes the model's predictions for the overall quantitative effects after the first year of the pandemic. The "Economy" columns report average daily percent changes relative to the corresponding pre-pandemic values. The baseline predicts that 13.8% of the population either has or has had COVID and that 1.6% still have COVID. The death toll stands at $6,592$. On the economic side, averaged over the year, employment fell 7.9%; output 5.7%. COVID relief payments are substantial: 3.5% of output. Finally, the welfare cost is measured at over 31% of consumption.

Table 2: Quantitative effects after one year

	Pandemic: Cases			Economy			
	Cumulative	Active	Deaths	Employment	GDP	$\frac{\text{Transfer}}{GDP}$	Welfare Cost
Baseline	13.79	1.60	6592	−7.85	−5.66	3.47	31.31
No interventions	51.00	1.04	26,614	−0.83	−3.66	0.34	56.25
Health only	22.00	0.99	11,688	−0.46	−1.17	0.18	40.46
Socioeconomic only	39.94	1.53	19,318	−23.61	−17.83	11.84	58.26
Stronger contagion aversion	9.66	1.05	4664	−5.57	−4.34	2.37	37.29
More sociable	17.60	2.18	8393	−9.79	−7.13	4.50	35.97
Tighter business restrictions	9.62	1.29	4809	−15.37	−10.86	7.46	29.34
Higher asymptomatic case rate	32.45	1.52	17,239	−18.46	−13.90	8.80	49.90
No testing	27.50	1.59	12,936	−15.88	−11.53	7.26	46.83
Flat contagion	21.35	1.12	10,126	−11.77	−8.50	5.30	41.92

Note: All in percent except deaths.

While the predictions under the baseline scenario are grim, things could have been worse. Absent health and socioeconomic interventions, the model predicts nearly a quadrupling in COVID cases, and a staggering death toll of over 26 thousand. While the employment and output effects are more modest, the welfare cost is higher at 58% of consumption.

On their own, the health interventions and the socioeconomic interventions predict epidemiological outcomes between those seen under the baseline and no-policy scenarios. The health policies have the least economic disruptions, but nonetheless a substantial welfare cost (40% of consumption).

In isolation, the socioeconomic policies have truly massive economic effects *and* the highest welfare cost (58%). While socioeconomic interventions are a blunt weapon in controlling the pandemic, they have favorable short-term effects. Health measures which more directly target the disease progression deliver better "medium term" results. The overall lesson is that health and socioeconomic interventions are complements, not substitutes, and the best outcomes are achieved when they are used in tandem.

Fig. 5 shows that under the baseline and health-only interventions, new cases and deaths were nearing zero early in the autumn while the no-policy and socioeconomic-only scenarios were not. These observations suggest that there are still important dynamics to consider beyond the first wave. Table 3 provides a summary at the one, two and three year horizons. (Given vaccine approvals in December 2020, the three year horizon is likely moot. The three year horizon can be thought of as capturing the effects of a previously more typical vaccine development cycle.) Under the baseline, fatalities rise from $6,592$ (first year) to 15.2 thousand (second year), and subsequently 16.4 thousand. The output loss in year 2 is substantial (-6.6%) while that in year 3 is more modest (-0.9%).

The no-intervention scenario sees a further increase in deaths in year 2, and a leveling off in year 3. Evidently, once 60% of the population has contracted COVID, herd immunity starts to kick in. Output losses in year 2 are still sizable, but vanish in year 3. As with the baseline, the health interventions alone see an increase in deaths in year 2, stabilizing in year

Table 3: Quantitative effects observed at the end of year 1, year 2, and year 3

	Pandemic						Economy		
	Accumulated cases (%)			Accumulated deaths			GDP (%)		
	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
Baseline	13.79	31.92	34.41	6592	15,156	16,351	−5.66	−6.62	−0.87
No interventions	51.00	60.86	61.79	26,614	31,363	31,813	−3.66	−0.43	0.01
Health only	22.00	34.38	35.36	11,688	17,513	17,993	−1.17	−0.48	−0.01
Socioeconomic only	39.94	58.36	61.21	19,318	27,965	29,328	−17.83	−6.81	−1.00
Stronger contagion aversion	9.66	25.79	31.28	4664	12,049	14,578	−4.34	−6.24	−2.08
More sociable	17.60	35.37	36.10	8393	17,117	17,486	−7.13	−6.59	−0.24
Tighter business restrictions	9.62	26.36	31.54	4809	12,575	14,964	−10.86	−20.00	−6.94
Higher asymptomatic case rate	32.45	49.98	52.46	17,239	25,502	26,692	−13.90	−6.42	−0.86
No testing	27.50	45.81	48.44	12,936	21,571	22,830	−11.53	−6.70	−0.92
Flat contagion	21.35	33.03	34.55	10,126	15,689	16,415	−8.50	−4.23	−0.52

3. Output losses are broadly similar to the no-policy scenario. By themselves, socioeconomic interventions result in nearly as many deaths as the no-intervention case, and larger output losses in years 2 and 3.

Tables 2 and 3 also report results for other parameterizations of the model, and other policies; time paths for the first year can be found in the supplementary figures appendix (Figs. A.1 and A.2). Three of these extra results operate on the socioeconomic side of the model. The first considers a doubling the "fear of death" parameter, ψ_d. Recall that the value of this parameter was calibrated using a value of a statistical life of \$5.2 million; doubling the value of ψ_d can be justified by doubling the value of a statistical life. Increasing this parameter leads agents to work less, and choose fewer social contacts. Relative to the baseline, there are 30% fewer deaths at the end of year 1. However, the difference narrows to 20% in year 2, and 10% by year 3.

Second, the preference parameter for social contacts, ψ_s, was calibrated using evidence from Sweden on the welfare cost of staying at home. Suppose that Ontarians are more sociable than Swedes by doubling the baseline value for ψ_s. Agents choose more social contacts which increases the number of cases and deaths by over 25%. The first year economic consequences are worse than the baseline, and the welfare cost of the pandemic higher.

Third, on the socioeconomic side of the model, the government has two levers: restrict social contacts, and close businesses. During the lockdown, social contacts are already at a minimum; suppose that the government more aggressively closed businesses in response to new cases: quadruple the value of the feedback parameter, η, in (14). Under this policy, more businesses are closed during the first year, and employment and output are consequently much lower. The welfare costs of the pandemic are slightly lower than the baseline while year 1 deaths are reduced by about a third. As with increased contagion aversion, the difference in deaths diminishes with time.

The remaining three results explore the implications of changes on the health side. The first considers the effects of a higher asymptomatic case rate. Early in the pandemic, some research placed this rate at 80%, double the more recent estimates. To this end, double the value of δ from 0.4 to 0.8. This scenario results in more infected individuals circulating in society since fewer people learn their COVID status (fewer exhibit symptoms). COVID cases and deaths more than double, the economic consequences over the first year are more than twice as large, and the first year welfare cost of the pandemic increases to nearly 50% of consumption.

Second, what if there were no testing ($\upsilon_t = 0$)? By allowing greater spread of the coronavirus, no testing reduces social welfare. Keep in mind that testing should be thought of as more than actual tests; it includes other measures like contact tracing and the isolation of detected individuals. Under this scenario, deaths nearly double. Due to the increased number of cases, there are more business closures, and so the economic effects increase.

Finally, suppose that there was no summer decline in contagion, and so α_t remains at 3/4 of its pre-pandemic value. This scenario also sees an increase in COVID cases and deaths in year 1 by over 50% relative to the baseline. Again, the business closure rule implies lower employment and output, and the welfare cost is commensurately higher. In years 2 and 3, results for the flat contagion probability case are little different from the baseline.

5 The second wave and lockdown

In the data, there is considerable variation in the number of daily deaths, as depicted earlier in Fig. 4. Nonetheless, in retrospect, it seems clear that COVID-related mortality started rising early in November 2020, and may have peaked in mid-January 2021. Given the lags in the disease progression, new cases must have started rising in October.

We can use the model to make inferences about when the second wave actually started, and so speculate as to its causes. Fig. 6 shows that the model predicts that the second wave actually started in early October when both new and active cases began rising. Deaths then follow with a lag. Indeed, the baseline model fits the late-2020 and early-2021 Ontario mortality data remarkably well.

In the model, the only change in the autumn is the rise in the contagion probability, mirroring the seasonal patterns for the cold and flu. According to the model, then, the second wave is the result of this increased likelihood of contagion. But what exactly does this autumnal pattern represent? Is it simply the fact that as it gets colder, people move activities from the airy outdoors to the less well-ventilated and more crowded indoors? Does it reflect the start of the school year? Hopefully others will take a closer look at the data to disentangle the potential explanations.

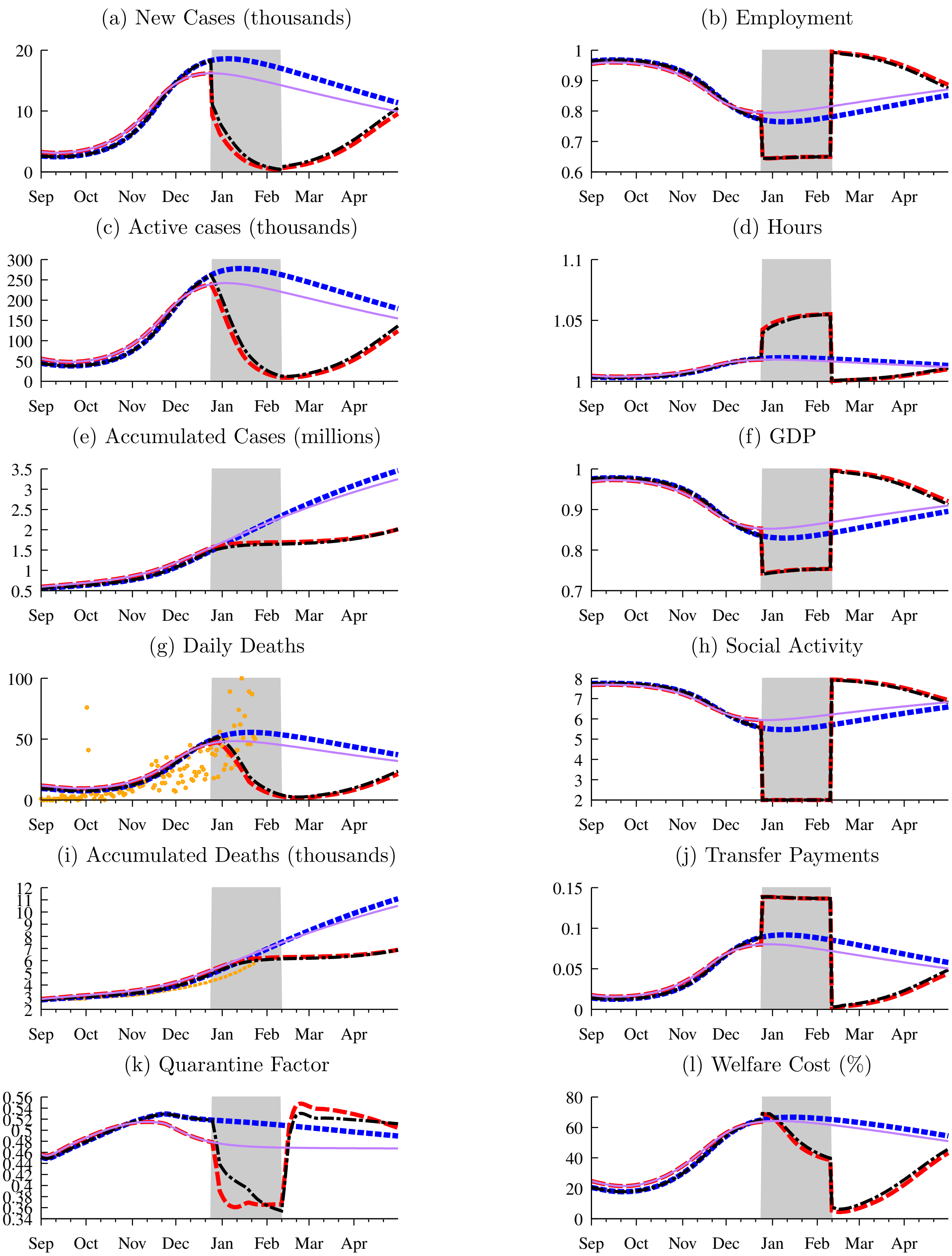
While the data suggest that peak mortality in the second wave is of a similar magnitude to that seen in the first wave, the model also suggests that (true) new and active cases are higher. The differences between the two waves reflects the decline in the infection fatality rate which we assumed fell through the lockdown period, reflecting changes in best practices in treating severely ill COVID patients. A consequence of the higher case rates is that it was likely more difficult to detect COVID-positive individuals. To capture this likelihood, suppose that the testing probability depends inversely on the number of known cases:

$$\upsilon_t = \underline{\upsilon} + \max\left\{0, (\overline{\upsilon} - \underline{\upsilon})\left(1 - \zeta \frac{N^{ik}_{t-1}}{N - N^{d}_{t-1}}\right)\right\}. \tag{35}$$

In (35), we set $\underline{\upsilon} = 0.01$ on the basis that *some* asymptomatic cases will be detected, even when the public health system is inundated with COVID cases. To capture the notion that the public health system has limited resources, set $\overline{\upsilon} = 0.04$; after all, it simply is not feasible to test the entire population every day, much less trace every contact of known cases. Finally, the parameter ζ reflects the sensitivity of testing to the fraction of known active cases in the population. We assigned a value of $\zeta = 65$ with an eye to maintaining roughly the same average testing probability during the first lockdown as under the baseline (3.5%), and to roughly matching Ontario's mortality data during the second wave.

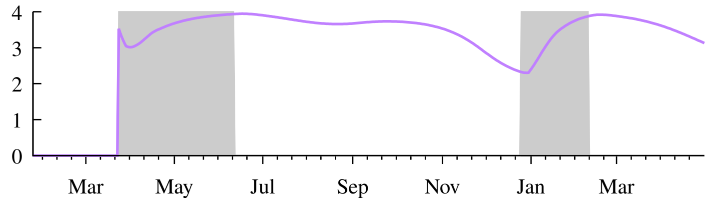
Such dependence of the testing probability on the number of cases reflects not only limits to the number of tests that can be conducted, but also limits to contact tracing (used to

Figure 6: Second wave scenarios



Legend: Baseline, solid purple; endogenous testing, dotted blue; baseline with second lockdown, dashed red; endogenous testing with second lockdown, dot-dashed black; lockdown, the shaded area.

Figure 7: Testing probability (%)



identify individuals who have been exposed to a COVID-positive person, and so at higher likelihood of being infected). As shown in Fig. 7, over the first wave, v_t fluctuates around 0.035, the value used in the baseline when testing is constant. However, starting in November, this testing probability starts to fall as cases rise. Relative to the baseline, this time-varying testing probability scenario predicts a somewhat later and higher peak in cases and fatalities, reflecting the effect of a lower testing rate when the contagion curve steepens.

To start, how would events transpire if the government takes no action? Under the baseline (solid purple lines in Fig. 6), peak new cases occurred on December 26 at 16.2 thousand. Active cases peak at 242 thousand early in January while the apex for daily deaths is 48 on January 11. When testing is given by (35) (dotted blue lines in Fig. 6, the high-water marks are 18.6 thousand new cases (January 5), 277.8 thousand active cases (January 14), and 56 daily deaths (January 21). Looking across these two scenarios points to the importance of testing and contact tracing. As these systems are put under strain, more people contract COVID and so more eventually die.

In response to rising COVID cases and deaths, on December 21, 2020, Ontario Premier Doug Ford announced a minimum 28 day lockdown starting Boxing Day. Under the lockdown orders, all schools were closed and only essential businesses were open. On January 12, 2021, a stay-at-home order lasting at least 28 days was announced, effective January 14. Schools were to remain closed until February 10.

To evaluate the likely effects of such a lockdown, the model is solved with only essential businesses open ($b_t = b_{\min}$) and minimal social interactions ($s_t = s_{\min}$) between December 26, 2020 and February 10, 2021. Results for the baseline with a second lockdown are given by the dot-dashed black lines in Fig. 6 while the dashed red lines correspond to the time-varying testing rate. The proximate effects of such a lockdown are, of course, minimal social and economic activity. Prior to the lockdown, the business openings rule, (14), prescribed that 80% of businesses should operate; this figure immediately falls to 65%. Due to the rise in unemployment, pandemic-related transfers nearly double. Owing to the plunge in employment, the marginal product of labor rises, driving up the real wage. In fact, the real wage rise is sufficient to push average hours worked by those with jobs above one, its pre-pandemic value.

Under the baseline, these measures result in an immediate drop in new cases, from 16.2 thousand per day to 9.3 thousand. Active cases and daily deaths subsequently fall, but at a more leisurely pace due to the gestational lags inherent to the disease progression. The story is much the same when testing is given by (35); under this scenario, new cases decline from 18.3 thousand to 11.1 thousand.

Fig. 6(l) indicates that just prior to the second lockdown, the welfare cost of the pandemic had risen to around 64% of daily consumption. Absent policy action, these costs remain at around this level. In the short term, the second lockdown pushes the welfare cost up by roughly 5 percentage points. However, as COVID cases and fatalities decline, so does the welfare cost of the pandemic. At the end of the lockdown, the welfare cost has fallen to 38.6% of daily consumption, compared to 61.7% with no lockdown. Averaged over the entire lockdown period, the effect of the lockdown is to *reduce* the welfare cost of the pandemic by 11.5 percentage points. After the lockdown, business activity is once again governed by the rule (14). At that point, new cases are sufficiently low that virtually all business are open, and social activity is very close to its pre-pandemic level. As a result, immediately after the second lockdown, the welfare cost is 'only' 5% of daily consumption – much better than the do-nothing scenarios under which the welfare cost continues to exceed 60%. In other words, the lockdown results in a welfare gain both *during* the lockdown, and in the months that immediately follow.

Worryingly, new cases are on the rise again starting in March, and a full-blown third wave is on the horizon. It may be tempting to say that a third wave is unlikely to develop given the current vaccination program. Based on expected vaccine deliveries, Canada's current vaccination plan calls for vaccinating only 8% of the population by the end of March, rising to $40 - 50\%$ by the end of June. Ontario can presumably expect much the same pattern of vaccinations. Such a schedule leaves a large proportion of the population still susceptible when the model predicts rising case numbers, precipitating a third wave.

6 Conclusion

We developed a model featuring interactions between socioeconomic activity, and the progression of the coronavirus pandemic. As COVID cases rise, individuals respond rationally by choosing to work less and having fewer social interactions in order to reduce the likelihood of contracting the disease. In turn, the collective actions of individuals implies a reduction in daily contacts, and so slow the progression of the coronavirus.

On the epidemiological side, our model departs from the textbook model by accounting how daily contacts affects the likelihood of contracting COVID, with these daily contacts being endogenously determined by socioeconomic considerations. Novel features on socioeconomic side include preferences over the number of social contacts, and a "fear of death" that succinctly captures epidemiological developments. The utility weight on the "fear of death" was calibrated using evidence on the value of a statistical life, while the weight on social interactions was determined by evidence from Sweden on the cost of social isolation.

In the model, the government has four instruments: restrictions on social activity; business closures; the contagion probability, reflecting public health measures like mask mandates and increased hygiene; and testing, capturing not only diagnostic testing, but also other measures such as contact tracing. The first two instruments can be characterized as socioeconomic ones, and the last two as public health. The model was calibrated so that when the government uses all four instruments, it broadly captures observed epidemiological and socioeconomic developments. Alternative model simulations evaluated the contributions of the health and socioeconomic interventions. Had the government used only one set of interventions, the model predicts far more fatalities. Socioeconomic policies are a blunt instrument in fighting the pandemic: they operate indirectly on disease progression and result in "collateral damage" in the form of high unemployment and social isolation. Nonetheless, our model finds that these measures are very effective in the short term, as seen in our analysis of the first and second lockdowns. In the model, health policies are more effective in longer term containment of the pandemic, and should be used in concert with short term application of socioeconomic interventions.

Our welfare cost calculation summarizes the various tradeoffs between health and socioeconomic interventions. According to our model, while the welfare cost of the pandemic under the baseline set of policies is substantial, this cost would have been even higher if only the health interventions had been used, and much higher if the only measures were socioeconomic. These results point to the complementarities between the health and socioeconomic interventions.

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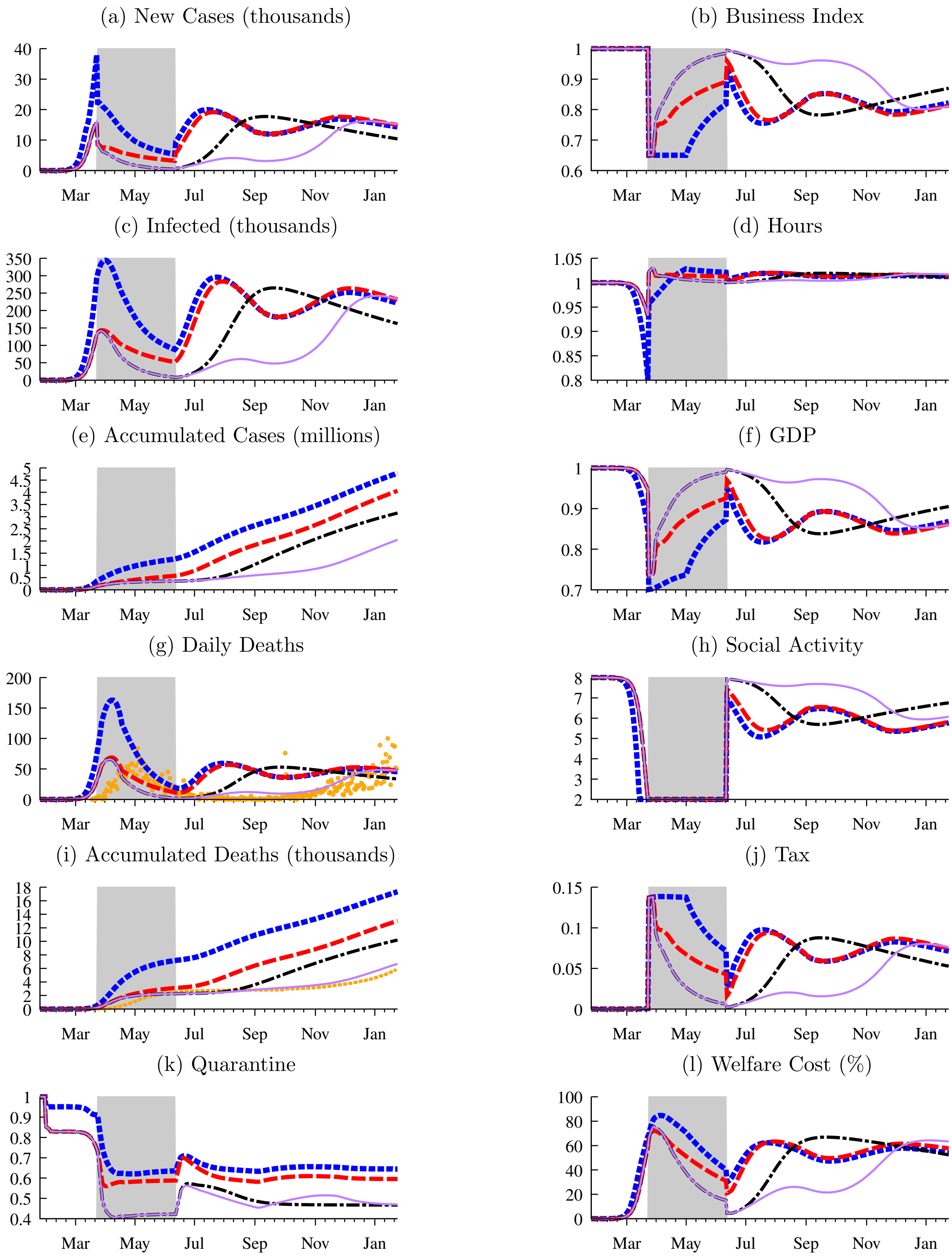
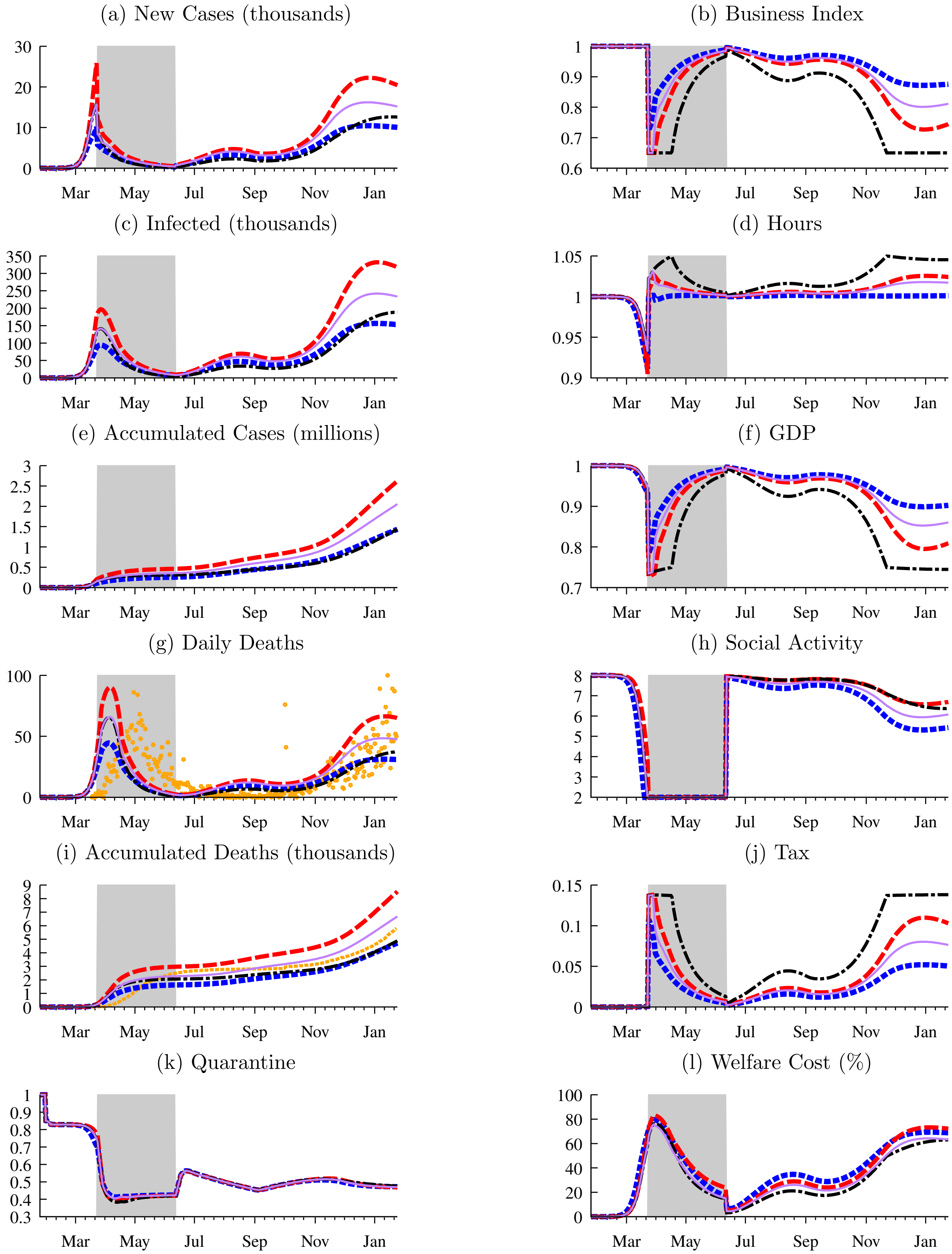
A Supplementary figures

Figure A.1: Alternative health scenarios.



Legend: Baseline, solid purple; higher asymptomatic case rate, dashed blue; no testing, dotted red; unchanged contagion probability, dot-dashed black.

Figure A.2: Alternative socioeconomic scenarios.



Legend: Baseline, solid purple; stronger contagion aversion, dashed blue; more sociable, dotted red; tighter business lockdown, dot-dashed black.