Appendix

A Model Appendix

A.1 Labor Supply

As explained in the main text we model a partial lockdown as a constraint on the share of total hours worked in the market (13).

Lemma 1 *Consider an individual with the preferences* (22)*, flexibility* ϕ *and facing an infection rate* $\dot{\mathcal{D}}$*. The lockdown constraint* (13) *binds whenever*

$$\kappa_\ell \leq \frac{\upsilon_\ell(\dot{\mathcal{D}})^{-\eta}}{\upsilon_\ell(\dot{\mathcal{D}})^{-\eta} + \phi^\eta}$$

and is slack otherwise. Therefore denote by

$$s_w = \min\left\{\kappa_\ell, \frac{\upsilon_\ell(\dot{\mathcal{D}})^{-\eta}}{\upsilon_\ell(\dot{\mathcal{D}})^{-\eta} + \phi^\eta}\right\}$$

the share of hours worked in the market. Total labor effort $\tilde{\ell}$ *satisfies a standard labor supply condition*

$$\varphi_\ell \tilde{\ell}^\nu c^\gamma = \tilde{w} \quad where \quad \tilde{w} = w(s_w + \phi(1-s_w))\Theta, \quad \Theta := \left(\upsilon_\ell(\dot{\mathcal{D}}) s_w^{\frac{1+\eta}{\eta}} + (1-s_w)^{\frac{1+\eta}{\eta}}\right)^{-\frac{\eta}{1+\eta}} \tag{A1}$$

is a wage index. Workplace hours, remote hours and total efficiency units of labor supplied by the household are given by

$$\ell_w = s_w \Theta \tilde{\ell}, \quad \ell_r = (1-s_w)\Theta\tilde{\ell}, \quad \ell := \ell_w + \phi \ell_r = (s_w + \phi(1-s_w))\Theta\tilde{\ell} \tag{A2}$$

When the lockdown constraint is slack, this collapses to $\tilde{w} = w\left(\upsilon_\ell(\dot{\mathcal{D}})^{-\eta} + \phi^{1+\eta}\right)^{\frac{1}{1+\eta}}$ *and*

$$\ell_w = \left(\frac{w/\upsilon_\ell(\dot{\mathcal{D}})}{\tilde{w}}\right)^\eta \tilde{\ell}, \quad \ell_r = \left(\frac{\phi w}{\tilde{w}}\right)^\eta \tilde{\ell}, \quad \ell = \left(\upsilon_\ell(\dot{\mathcal{D}})^{-\eta} + \phi^{1+\eta}\right)^{\frac{1}{1+\eta}} \tilde{\ell}. \tag{A3}$$

For example with a complete lockdown $\kappa_\ell = 0$, we have $\Theta = 1$ and hence

$$\ell_w = 0, \quad \ell_r = \tilde{\ell}, \quad \ell = \phi\tilde{\ell} \quad \tilde{w} = \phi w$$

as expected.

For some occupations, we want to set $\phi = 0$. In this limit the constraint binds, $s_w = \kappa_\ell$, and

$$\varphi_\ell \tilde{\ell}^\nu c^\gamma = \tilde{w} \quad \text{where} \quad \tilde{w} = w\kappa_\ell \Theta, \quad \Theta := \left(\upsilon_\ell(\dot{\mathcal{D}}) \kappa_\ell^{\frac{1+\eta}{\eta}} + (1-\kappa_\ell)^{\frac{1+\eta}{\eta}} \right)^{-\frac{\eta}{1+\eta}}$$

$$\ell_w = \kappa_\ell \Theta \tilde{\ell}, \quad \ell_r = (1-\kappa_\ell)\Theta \tilde{\ell}$$

There are two cases: a complete lockdown $\kappa_\ell = 0$ and a partial lockdown $\kappa_\ell > 0$. In a complete lockdown obviously all ℓ's are zero and in particular $\ell_r = 0$. In a partial lockdown $\ell_r > 0$. So this has the somewhat odd feature that even with $\phi = 0$ individuals still exert remote labor effort even though their remote labor is completely unproductive.

A.2 Problem of Critically Ill

We here spell out in more detail the problem of the critically ill, i.e. those in the $\mathfrak{h} = \mathfrak{c}$ health state, briefly discussed in Section 2.2. It complements the problem of individuals in the $\mathfrak{h} = \mathfrak{l}$ health state discussed there (meaning all remaining individuals who are in one of the $\mathcal{S}, \mathcal{E}, \mathcal{I}$ and $\mathcal{R}$ groups and able to work). The main difference relative to the problem of able individuals is that the critically ill are in the ICU are thus unable to work, i.e. their labor income is zero. Because they have no labor income we assume that the government provides them with fixed amounts of regular and social consumption $\underline{c}$ and $\underline{s}$. Their period utility is therefore

$$U(\underline{c}, \underline{s}, 0) - V(0,0,0).$$

Note in particular that the critically ill do not make any consumption or labor supply choice. Since the government pays for the consumption needs of the critically ill their liquid and illiquid assets evolve according to

$$\dot{b}_t = r_t^b b_t + T_t - d_t - \chi(d_t, a_t) \tag{A4}$$

$$\dot{a}_t = r_t^a a_t + d_t \tag{A5}$$

$$b_t \geq 0, \qquad a_t \geq 0. \tag{A6}$$

Note that we do allow for the possibility of the critically ill rebalancing their portfolios by depositing and withdrawing (d_t) but this is the only choice they get to make.

A.3 Sticky Prices

B Data Appendix

B.1 Details of Occupation Classifications

Our starting point is the 430 occupations classified based on the 5-digit 2010 SOC system. Employment and average wages for each occupation are computed from the May 2017 Occupational Employment Statistics (OES) data collected by the Bureau of Labor Statistics (BLS). The OES collects information on occupations by industry and allows to compute employment shares and average wages of each occupation in the c and s sector.[41]

Our occupational flexibility index is the binary "teleworkable" indicator computed by Dingel and Neiman (2020a) based on O*NET data. The vast majority of their 5-digit SOC level indeces are either 0 or 1 but, because the indicators are originally constructed at a higher level of disaggregation, some of them equal 0.25, 0.5 and 0.75. We set the 0.25 to 0 and 0.75 to 1. We reassign either a 0 or a 1 to those equal to 0.5 based on the value of the teleworkable indicator for the closest occupations.[42] To gain confidence that our classification is robust, we also computed an alternative index of flexibility based on the American Time Use Survey (ATUS). Our sample consists of respondents to the 2017-2018 ATUS Leave Module. This module by construction excludes all non-workers and all self-employed workers and has a sample size of 9,456 workers. We classified an individual job as flexible if the individual responded "YES" to the question (LUJF_10): *As part of your (main) job, can you work at home?* We then aggregate these aswers by occupation, using ATUS-provided weights (LUFINLWGT). This analysis can only be done at the 3-digit SOC level because of the small sample size of ATUS. Thus, for comparison, we also aggregate the Dingel-Neiman indicator (no longer binary, but a continuous variable between 0 and 1) at the 3-digit level using employment shares. There is a strong agreement between the two indeces as seen in Figure B1, a weighted scatterplot of the two indicators across 3-digit occupations. The employment-weighted correlation is over 0.80.[43]

The Department of Homeland Security (DHS) published a memo containing a list of "critical infrastructure workers" (not corresponding to any particular SOC classification,

[41] A full list of occupations is available here https://www.bls.gov/soc/2018/home.htm. From the initial set of occupations we exclude major group 55 known as *Military Specific Occupations* and other 13 occupations for which reported OES employment for that month is zero.

[42] There is a handful of occupations (in their Table A.1) in which task-based O*NET indicators differ from "manually imputed measures based on introspection" by the authors. For those, we use the latter indicator which seems more reasonable.

[43] The biggest gaps between the two indicators in each direction are for: Other Education, Training, and Library Occupations (where the ATUS flexible share is 75 ppt smaller than the O*NET one) and Occupational Therapy and Physical Therapist Assistants and Aides (where the ATUS flexible share is 75 ppt bigger than the O*NET one).

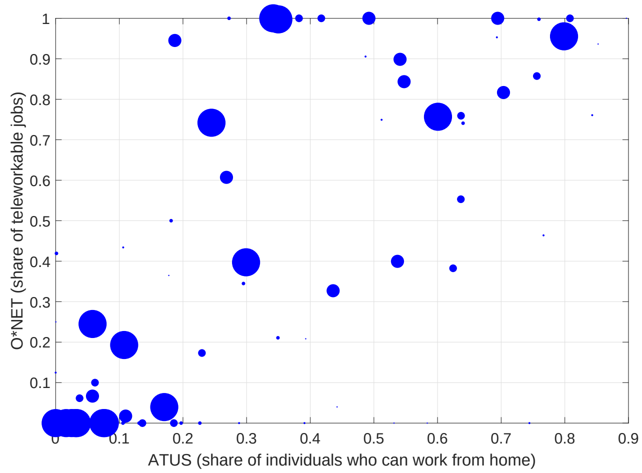

Figure B1: Weighted scatterplot of O*NET and ATUS indicators for flexible jobs across 3 digit occupations.

unfortunately). Tomer and Kane (2020) compiled a list of 121 4-digit NAICS industries that relates to this DHS list. We map these industries into occupations using the 5-digit occupational employment-by-industry OES dataset for 2017. Thus, for each of the 443 occupational groups, we obtain the share of critical workers in that group.

The notion of essential occupations relevant to us is that the lockdown does not extend to those critical workers but, if it did, they would be unable to perform their tasks. Since flexible occupations are barely affected by the lockdown, as their workers can easily shift from onsite to remote mode, we define an occupation as essential if it is critical *and* not teleworkable. In practice, this group includes Nurses, Flight Attendants, Police Officers, Subway Operators, Postal Service Workers, etc.[44] When we compute statistics for essential occupations, we average across all occupational group by weighting each of them by their share of essential workers.

The final data set contains, for each 5-digit occupation, the share of essential workers (between 0 and 1), a binary indicator for flexibility, together with employment and average earnings for that occupation in the c and s sector.[45]

To calibrate the model, we need also need to define 'C-intensive' and 'S-intensive' for an occupation. We do it based on its relative labor share in the two sectors (with a threshold of 1). Finally, we need to further split C-intensive and S-intensive occupations into two

[44] There exists an alternative definition of critical occupations compiled by the LMI Institute (Vivalt, 2020) which maps directly into the related 6-digit SOC occupational definitions. mapping directly into occupations, though, is problematic. For example, according to this definition, Cooks are a critical occupation probably because some critical infrastructures need cooks e.g. hospitals). In our preferred definition, instead, only 10% of cooks are essential.

[45] For most occupations, employment is heavily concentrated in one of the sectors. However, for some (e.g., janitors, secretaries) employment shares in the two sectors are more similar. The employment-weighted correlation between occupational wage in the two sectors is 0.974.

groups according to whether they are flexible or not. For this last step, we use the Dingel-Neiman indicator. This procedure yields a total of 5 occupational groups: essential ($j = E$), C-intensive flexible ($j = CF$), C-intensive rigid ($j = CR$), S-intensive flexible ($j = SF$), S-intensive rigid ($j = SR$). For each group, we compute employment share and average wage as well as sectoral labor shares. Table 4 summarizes these statistics and lists some examples for these five groups.

B.2 SIPP

We use Waves 1-4 of the 2014 SIPP. For each wave, we select all individuals of age 15 or older who were present in all 12 months of the wave. The waves are treated separately when computing all intermediate variables, and then pooled prior to final estimation. We do not link individuals across waves in any way.

Respondents to SIPP are allowed to provide up to seven distinct jobs, each of with is reported for the individual months out of the year during which the individual held said occupation. For each worker-wave pair, we classify a worker as holding a given occupation by identifying as the primary occupation the occupation code reported in the greatest number of months. We then assign an occupation to the household based on the occupation of its primary earner. Since the SIPP occupation codes don't exactly match one-to-one with the SOC 5-digit codes (though they are nerly the same): (1) A very small number of 5-digit SOC categories do not appear anywhere in SIPP. (2) Because of some aggregated SIPP occupation codes, a handful of occupations are 3-digit occupations not 5-digit. The teleworkable score is constant across 5-digit occupations within each of these 3-digit categories so there is no loss of information there.

Individual labor earnings are defined as income earned from all jobs worked during the month, including wage and salary income, bonus payments, commissions, overtime payments, tips, other income from self-employed businesses, self-employed business profits, and accounting for time spent away from a job without pay.

We use the following definitions for assets and liabilities:

$$\begin{aligned}
\text{Deposits} &= \text{saving accts} + \text{checking accts} + \text{money market funds} \\
\text{Bonds} &= \text{gov bonds} + \text{municipal and corporate bonds} \\
\text{Liquid assets} &= 1.05 \times (\text{deposits} + \text{directly held bonds, stocks and mutual funds}) \\
\text{Net liquid assets} &= \text{liquid assets} - \text{credit card debt} \\
\text{Net illiquid assets} &= \text{home equity} + \text{IRA} + \text{Keogh} + \text{CDs} + \text{life insurance}
\end{aligned}$$

All estimates are computed based on the provided household-level weight variable for the 2014 SIPP [XYZ].

B.3 The static elasticity of substitution between c and s

$$
\begin{aligned}
c_t^{-\gamma} &= \lambda_t P_{ct} && \text{(B1)}\\
\varphi_\ell \left(\ell_{wt}\right)^{\zeta} &= \lambda_t \left(1-\tau\right) w_t z_t && \text{(B2)}\\
\varphi_s \left(s_t^{\frac{\theta-1}{\theta}} + h_t^{\frac{\theta-1}{\theta}}\right)^{\frac{1-\gamma\theta}{\theta-1}} s_t^{-\frac{1}{\theta}} &= \lambda_t P_{st} && \text{(B3)}\\
\left(s_t^{\frac{\theta-1}{\theta}} + h_t^{\frac{\theta-1}{\theta}}\right)^{\frac{1-\gamma\theta}{\theta-1}} h_t^{-\frac{1}{\theta}} &= \varphi_h && \text{(B4)}
\end{aligned}
$$

where λ_t is the multiplier on the budget constraint. Using the second optimality condition into the first one, rearranging and taking logs we obtain:

$$
\log\left(\frac{c_t}{s_t}\right) = const - \frac{1}{\gamma}\log\left(\frac{P_{ct}}{P_{st}}\right) + \frac{\gamma\theta-1}{\gamma\left(\theta-1\right)}\log\left[1+\left(\frac{\varphi_\ell\left(\ell_{wt}\right)^{\zeta}}{\varphi_h}\cdot\frac{P_{st}}{\left(1-\tau\right)w_t z_t}\right)^{\theta-1}\right], \quad \text{(B5)}
$$

where the constant is $(-1/\gamma)\log\left(\varphi_s\right)$. This equation implies that, in absence of h, the static elasticity of substitution between c and s would be $1/\gamma$, i.e. equal to to the intertemporal elasticity. In the presence of h, $1/\gamma$ regulates the elasticity of substitution between c and the (s,h) bundle. Thus in ($B5$) there is an extra term that reflect the fact that, for given change in the relative price P_{ct}/P_{st}, a change in P_{st} relative to the price of home-production (the after-tax wage) will also affect the expenditures on s and therefore the ratio of quantities on the left-hand-side. Recall that $\gamma \geq 0$ and $\theta \geq 1$, thus the sign of this effect is ambiguous.

When we estimate equation ($B5$), we abstract from heterogeneity in z. We therefore replace $w_t z_t$ with the average hourly wage at date t and ℓ_{wt} with average hours worked in the market at date t. As a result this first-order condition is the same across all households and we can use aggregate quantities on the left-hand-side, Y_{ct} and Y_{st}.[46]

From the BEA website, Interactive Access to Industry Economic Accounts Data: GDP by Industry web page, we obtain value added by industry in nominal terms and chain-type price indeces for value added by industry from 1963-2019. Let va_{it} be the nominal value added in industry i. Let I_s be the set of industries in s and I_c the set of industries in c, based on the classification in Table 3. Next, we construct a time series for value added in the c and s sectors:

$$
VA_{jt} = \sum_{i\in I_j} va_{it},\ j \in \{c,s\}.
$$

Let p_{it} be the price index for industry i in year t. We want to compute a price index for

[46] The series for wages is hourly compensation (PRS85006103). Average hours per person are computed as the total hours (B4701C0A222NBEA) divided by employment (CE16OV) and multiplied by the employment to population ratio (LNS12300000). All series were retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series on April 23, 2020.

	1963-2019	2000-2019	HP filter (1963-2019)	BK filter (1963-2019)
$\hat{\gamma}$	0.805 (SE 0.136)	0.781 (SE 0.057)	1.387 (SE 0.235)	0.916 (SE 0.159)

Table 8: Alternative estimates of γ.

each sector, call them P_{ct} and P_{st}. We use a Tornquist index, i.e.

$$\begin{aligned} \Delta \log P_{jt} &= \log\left(\frac{P_{jt}}{P_{j,t-1}}\right) = \left[\frac{1}{2}\sum_{i\in I_j}\left(\frac{va_{it}}{VA_{jt}} + \frac{va_{i,t-1}}{VA_{j,t-1}}\right)\log\left(\frac{p_{it}}{p_{i,t-1}}\right)\right] \\ P_{jt} &= P_{j,t-1}\exp\left(\Delta \log P_{jt}\right), \text{ with } P_{j0} = 1 \text{ (a normalization).} \end{aligned}$$

Next, we deflate value added to compute quantities of the c and s goods:

$$Y_{jt} = \frac{VA_{jt}}{P_{jt}},\ j = \{c, s\}.$$

We set $\theta, \tau, \zeta, \varphi_\ell$ and φ_h to our calibrated values. We run 4 separate regressions. In the first regression we use the entire sample period and add a time trend which captures low-frequency movements in relative taste for the s good (φ_s). In the second, we restrict attention to the most recent years, post 2000. In the last two, we run the regression on filtered time series to isolate the business cycle component, since we are mostly interested in short-run substitutability. We use an HP filter (smoothing parameter =100) and a Baxter-King band-pass filter (2-8 years). The results are presented in Table 8.

All the point estimates for γ are quite close to 1, which is reassuring given our choice of $\gamma = 1$ for the intertemporal elasticity of substitution.

B.4 Calibration of preference feedback using VSL estimates

Recall the meaning of the value of statistical life (VSL). Suppose each person in a sample of 10,000 people were asked how much they would be willing to pay for a reduction in their individual risk of dying of 1 in 10,000 over the next quarter. Since this reduction in risk means that we would expect one fewer death among the sample of 10,000 people on average over the next quarter, this is sometimes described as "one statistical life saved." Suppose that the average response to this hypothetical question is \$1,000. Then, the total dollar amount that the group would be willing to pay to save one statistical life next quarter would be \$1,000 per person × 10,000 people, or \$10 million. This is the estimated VSL.

The key object of interest in the VSL literature is the semi-elasticity of hourly wages to fatality risk across occupations, i.e. the parameter β_0 in the following linear regression:

$$\log w_{it} = \beta_0 \dot{\mathcal{D}}_{it} + \beta_1 X_{it} + \varepsilon_{it}, \tag{B6}$$

which measures the monetary compensation for a marginal increase in fatality risk of one unit. For example, assume that the estimated value of $\hat{\beta}_0$ is 660. To translate this estimate into a VSL one has to multiply $\hat{\beta}_0$ by mean quarterly earnings ($15,000) which yields a VSL of 10M. Empirical estimates of $\hat{\beta}_0$ of that magnitude are common in this literature, and this is how the literature arrives at VSL of the order of 10M.[47]

One issue in mapping existing estimates of β_0 for linear models to our framework is that in our model the relationship (25) is nonlinear in the death rate. Equation 25 implies that the marginal compensation for an additional unit of risk evaluated at a death rate $\dot{\mathcal{D}}^*$ is:

$$\beta_0(\dot{\mathcal{D}}^*) = \left(\gamma_\ell^0 \nu_\ell^0 \nu_\ell^1\right) \left(\dot{\mathcal{D}}^*\right)^{\nu_\ell^1 - 1} \tag{B7}$$

and it depends on the level of fatality risk. The implied VSL also depends on the level of the death rate and is computed by multiplying $\beta_0(\dot{\mathcal{D}}^*)$ by mean quarterly earnings ($15,000).

As explained in the main text, we want to match a VSL of 10M for a death rate around 1/10,000 per quarter and a VSL around 4M for a death rate around 1/1,000 per quarter based on the estimates in Lavetti (2020). Given $\gamma_\ell^0 = \frac{\eta(1+\zeta)}{1+\eta} = 1.99$, these two moments can be matched with the pair $\nu_\ell^0 = 8$ and $\nu_\ell^1 = 0.6$.

C Details on Fiscal Stimulus Package in Data and Model

The Coronavirus Aid, Relief, and Economic Security Act, also known as the CARES Act was passed by U.S. Congress and signed into law by President Trump in late March 2020 in response to the economic fallout of the COVID-19 pandemic. It included several elements directed to cushioning the economic consequences of the contraction on households.

The **Economic Impact Payments (EIP)** program consisted of stimulus transfers with amounts which depended on family size and were phased out at high income levels: $2,400 to each married couple filing jointly or $1,200 to each individual, and $500 for each dependent child under age 17. Those with adjusted gross income over a threshold received a reduced amount. The initial amount is reduced by 5% of adjusted gross income over the threshold. The threshold for those filing as single or married filing separately is $75,000; for those filing as head of household, the threshold is $112,500; and for married filing jointly, the threshold is $150,000. The total outlays reported by the Department of Treasury was $260B.

[47] Often, in empirical regressions the death risk is expressed per 10,000 units. In this case the equivalent estimate of β_0 would be 0.066 and to obtain a VSL of 10M one has to multiply $\hat{\beta}_0$ by mean quarterly earnings ($15,000) times by 10,000.

Based on these features, in the model, we phase out this program at the 95th percentile of income, and set the size of the payment per household to $1,900 in order to match total outlays.

We model these payments as flow transfers paid out evenly over 1.5 months starting from mid April. This allows us to capture delays that occurred during the rollout of the program and heterogeneity in the exact timing of the payments. See, e.g. https://www.cbsnews.com/news/stimulus-check-delays-payment-status-not-available/.

The CARES Act included several expansions to the **Unemployment Insurance (UI)** program. Federal Pandemic Unemployment Compensation (FPUC) entails an additional $600 per week for those already receiving unemployment benefits. Pandemic Emergency Unemployment Compensation (PEUC) adds an extra thirteen weeks of benefits for those who have exhausted unemployment benefits. Pandemic Unemployment Assistance (PUA) broadens eligibility to any individual who is out of work due to the pandemic, including formerly self-employed, contract, and gig workers ordinarily excluded from UI.

We model UI as transfers that compensate for the shortfall of individuals' labor incomes relative to their steady state values, based on the replacement rates by earnings decile calculated by Ganong et al. (2020, Figure 3). Let $y(j,z)$ be the average earnings (where the dispersion comes from heterogeneous wealth holdings) for workers in occupation j with individual productivity z. Let the $\bar{}$ symbol denote steady-state. Let $\rho(j,z)$ denote the replacement rate. When the policy is implemented, at date t along the transition the cum-benefit earnings equal $\max\{\bar{y}(j,z) \times \rho(j,z) - y_t(j,z), 0\}$. We assume the program starts in mid April expires on August 1st.

The **Paycheck Protection Program (PPP)** is a $669 billion small-business forgivable loan program which was administered in two tranches of $349 billion and $320 billion. The initial deadline for application was set to June 30, but it was later extended to August 8, 2020. PPP loans are designed to provide funds to small businesses to maintain their employment and wage rates similar to pre-crisis levels. The definition of mall business is 500 or fewer employees on average over a year, but it can be higher or lower depending on the industry. Additionally, sole proprietors, independent contractors, and other self-employed individuals are eligible for PPP loans.

In order to receive loan forgiveness, firms must have qualifying expenses (payroll, utilities, rent, and mortgage payments) that are at least as large as the loans. This criterion suggests that the loans are very likely to be forgiven, which is what we assume.

As explained in the main text, some researchers have argued that PPP may not have been as effective at protecting employment as the program's name suggests since firms are not required to demonstrate that funds provided under the program are used to finance payroll expenses for workers that would have been otherwise laid-off. Because of this moral hazard element, we model the PPP as part wage subsidy and part profit subsidy, with each component amounting to 50% of the PPP's budget. Figure 12 illustrates the exact values for the two subsidy rates, in the model. We assume the PPP starts in mid April expires on August 1st.

The CARES Act also **waived the 10% tax penalty for early distributions** from IRAs, 401(k) plans, and other retirement accounts if the individual or someone in the family contracts the virus or if the individual experienced adverse financial consequences (e.g., layoff, reduced work hours, or inability to work due to child-care needs) because of the virus. The bill also doubles the maximum amount of a loan from an employer-sponsored 401(k) retirement plan from \$50,000 to \$100,000 and allows up to a one-year delay in repayments of outstanding retirement plan loans. We model this policy as a reduction of 25% in the scale parameter χ_1 in the adjustment cost function in equation (20). We assume this policy is in place from mid April to August 1st.

D Additional Tables and Figures

Policy	Duration (months)	Fatality Rate (%)	Economic Welfare Cost Mean	p10	p90	E	CF	CR	SF	SR
Laissez-faire	–	0.33	2.31	1.29	3.3	2.51	1.63	1.76	2.88	2.71
Lockdown	2	0.23	3.36	2.17	4.46	3.44	2.63	3.04	3.88	3.84
	12	0.17	6.68	4.45	8.57	6.4	5.79	7.01	7.08	7.44
	17	0.05	7.63	5.05	9.63	7.16	6.86	8.31	7.87	8.43
Lockdown + Fiscal Stimulus	2	0.24	2.7	0.79	4.55	2.91	2.85	2.83	3.38	1.92
	12	0.17	5.94	2.88	8.38	5.92	6.11	6.78	6.64	5.07
	17	0.05	6.87	3.36	9.58	6.7	7.28	8.12	7.5	5.79
Lockdown C-sector Exempt	2	0.23	3.0	1.86	4.15	3.12	2.34	2.35	3.56	3.54
	12	0.18	5.29	3.6	7.07	5.17	4.6	4.24	5.86	6.35
	17	0.09	5.87	4.0	7.9	5.63	5.32	4.72	6.36	7.09
Social Consumption Tax	2	0.23	2.87	1.52	4.07	3.59	2.63	3.03	2.81	2.1
	12	0.17	4.66	1.04	8.72	7.18	5.88	7.07	2.54	0.01
	17	0.04	4.96	−0.37	10.01	8.24	6.99	8.4	1.82	−1.45
Workplace Hours Tax	2	0.24	2.68	1.58	3.7	2.99	2.15	2.43	3.42	2.56
	12	0.19	3.93	2.09	5.78	4.6	3.87	4.54	5.26	2.23
	17	0.11	4.06	1.97	6.26	4.86	4.36	5.11	5.55	1.59

Table 9: Cumulative death rates and distribution of welfare costs under actual and counterfactual scenarios considered.

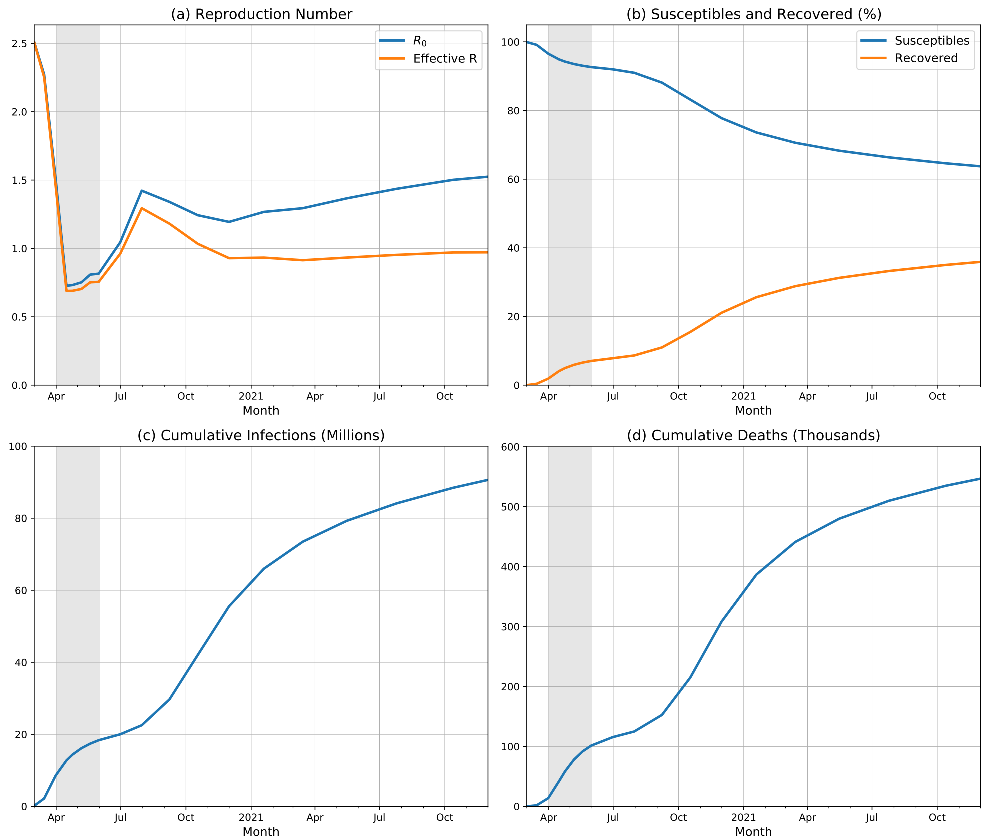

Figure D1: Model predictions for key epidemiological variables. Panels (c) and (d) plot the numbers of people for cumulative infections and deaths, interpreting the relevant population as the U.S. adult population of roughly 250 million people. For example, our model predicts roughly 350,000 COVID-19 deaths by January 1, 2021, broadly in line with epidemiological projections. For example this number is somewhat below the 410,000 COVID-19 deaths by January 1, 2021 predicted by the Institute for Health Metrics and Evaluation (IHME), see https://covid19.healthdata.org/united-states-of-america – website accessed on September 10, 2020.

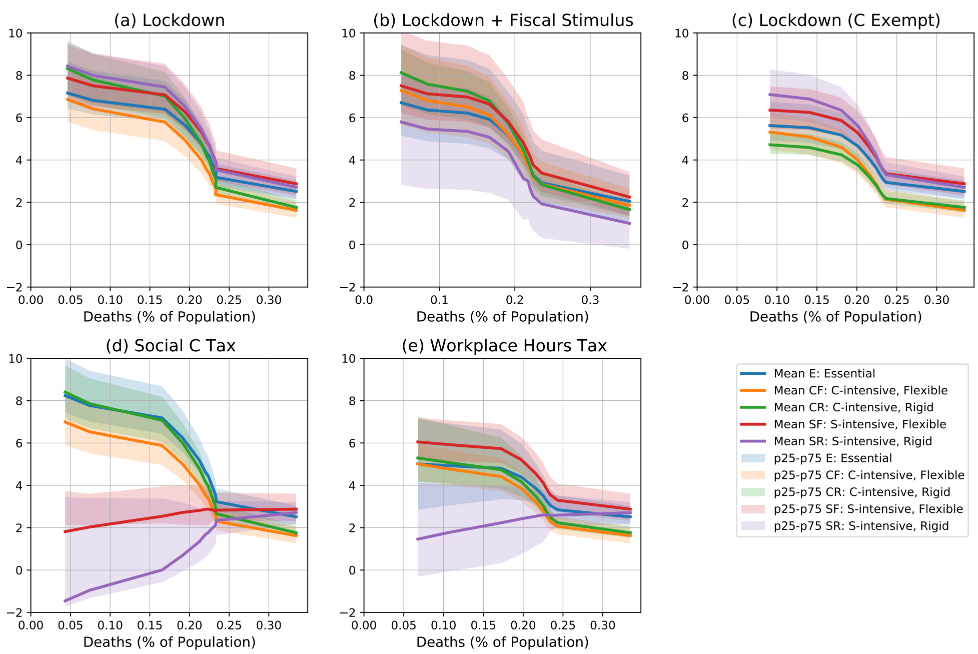

Figure D2: Distributional pandemic possibility frontiers by occupation for the five main experiments. Each line traces the mean economic welfare loss for each of the five occupations at any given cumulative aggregate death count.