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Macroeconomic Dynamics and Reallocation in an Epidemic: Evaluating the "Swedish Solution"*

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Abstract

In this paper, we argue that endogenous shifts in private consumption behavior across sectors of the economy can act as a potent mitigation mechanism during an epidemic or when the economy is re-opened after a temporary lockdown. We introduce a SIR epidemiological model into a neoclassical production economy in which goods are distinguished by the degree to which they can be consumed at home rather than in a social, possibly contagious context. We demonstrate that within the model the "Swedish solution" of letting the epidemic play out without government intervention and allowing agents to shift their consumption behavior towards relatively safe sectors can lead to substantial mitigation of the economic and human costs of the COVID-19 crisis. We estimate the model on Swedish health data and then show that compared to a model in which sectors are assumed to be homogeneous in their infection risk, as in Eichenbaum, Rebelo, and Trabandt (2020), endogenous sectoral reallocation avoids more than 2/3 of the decline in aggregate output and consumption, and at the same time induces a dynamics of weekly death that accords very well with the matching and of the number of deaths within one year. Our analysis implies case fatality rates below 0.2 percent and a limit of less than 800 deaths per million for Sweden. We also characterize the allocation a social planner would choose that can dictate sectoral consumption patterns and demonstrate that the laissez-faire outcome with sectoral reallocation, while mitigating the economic and health crisis, still implies suboptimally many deaths and too massive a decline in economic activity.

Keywords: Epidemic, Coronavirus, Macroeconomics, Sectoral Substitution

JEL classification: E52, E30

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1 Introduction

The COVID-19 pandemic of 2020 has the world in its grip. Policy makers had to wrestle with a serious trade-off: how much economic activity should one allow, possibly risking hundreds of thousands additional deaths as a result? The policy response was swift, but varied, with many countries around the world effectively shutting down their economies for extended periods of time in the spring and summer of 2020, whereas other countries adopting policies that let the pandemic run its course without much government intervention. Perhaps the most pointed example in the latter group is Sweden, which has largely avoided government restrictions on economic activity, allowing people to make their own choices. One can reasonably argue that Sweden was not as extremely laissez-faire as just described: the Swedish government provided many guidelines and recommendations to its citizens, and the Swedish population largely followed these, in order to mitigate the covid-19 spread. Nonetheless, the Swedish approach differed significantly from the lockdowns and restrictions imposed by other countries. For the purpose of this paper and our analysis and for comparison to Swedish data, we will therefore interpret the "Swedish Solution", as this laissez-faire extreme, in which the government does not intervene in the economic adjustments of private behavior and the economy as a whole to the epidemic.

In this paper we evaluate to what extent consumers concerned about their health, even in the absence of government intervention, will seek to mitigate economic interactions that carry the risk of infection, given the potentially disastrous consequences for their health? We then deduce the macroeconomic and public health consequences from the "Swedish Solution".

Our starting point is a simple macroeconomic model, where agents consume and work, combined with an SIR ("Susceptible-Infected-Recovered") model standard in the epidemiology literature. Our starting point is the model of Eichenbaum et al. (2020), ERT for short from now on, in which infections can occur in the market place by consuming together or working together. Individuals participating in these market activities are aware of the resulting infection- and death-risks, and thus may alter their consumption and work patterns as the epidemic unfolds, but do not take into account the externality of their behavior on the infection risks of others. Like them, we view the endogenous response in behaviour of people, motivated by their own interest in preserving their health and avoiding the possibility of dying, as key in understanding the spread of a pandemic and, ultimately, its economic costs, a significant advance from the purely epidemiological models beautifully summarized in Atkeson (2020).

We depart from ERT in one crucial dimension, however. In contrast to them we assume the economy is composed of several heterogeneous sectors that differ technologically in their infection probabilities. There are two interpretations of this assumption. One is, that very similar goods can be consumed in privacy at home (Pizza delivery) rather than in the market place (Pizza restaurant). Likewise, very similar work may be performed remotely rather than in an office, e.g. writing a report online at home rather than in the community of co-workers. The key mechanism of our model is the endogenous, privately optimal reallocation of individuals towards less contagious consumption activities and away from sectors in which consumption (or production) is subject to larger Covid-19 infection risk.

To support the empirical relevance of this mechanism we turn to Leibovici et al. (2020) who provide evidence for very substantial heterogeneity across sectors of the U.S. in the degree of social interaction to facilitate the production of goods and services. Dingel and Neimann (2020) as well as Mongey and Weinberg (2020) assess what share of jobs can be performed at home, and Toxvaerd (2020) provides an equilibrium in which social distancing is an equilibrium outcome emerging from individually rational behavior. Consistent with our main mechanism, Farboodi et al. (2020) provide evidence from US micro-data for a large reduction in social activity by private household even prior to the implementation of public stay-at-home-orders and lockdowns of economic activity.

For Sweden, Figure 1 displays seasonally adjusted monthly consumption expenditures on restaurants as well as on groceries, together with total consumption. There is clear evidence of reallocation of consumption activities away from food consumption in restaurants and towards food consumption at home, as proxied by expenditures on groceries. Aggregate consumption fell by 10% between February and April 2020, whereas consumption in restaurants collapsed by 50%. In contrast, expenditures on groceries actually increased 5% between February and March, and held steady thereafter. It is this reallocation between sectors, or modes of consumption that is at the heart of our quantitative dynamic equilibrium model.

How potent this reallocation mechanism is quantitatively depends crucially on the degree to which goods in different sectors are substitutable, as measured by the elasticity of substitution across goods (or work activities), which we denote by η in our paper. If different sectors are interpreted simply as different modes (food at home, food in restaurants) in which otherwise similar goods are consumed, then this elasticity can be assumed to be high. An alternative interpretation is that these sectors represent rather distinct goods or distinct lines or work, and that substitutability among them may be lower. We initially follow this interpretation and choose $\eta = 3$, following Adhmad and Riker (2019). We also consider a higher value, $\eta = 10$ as our benchmark, following Fernandez-Villaverde (2010). In both cases we assume that the economy is composed of two equally sized sectors that simply differ in their infection risk. Our parameterization implies that the infection probability in the most infectious sector (for the same consumption or work intensity) is nine times as high as in the least infectious sector.

Note that we interpret the term "consumption" in this paper broadly and applicable to non-market social activities as well. The substitution discussion above is relevant just as much for partying together with friends as opposed to talking online, for congregating in parks as opposed to staying at home,

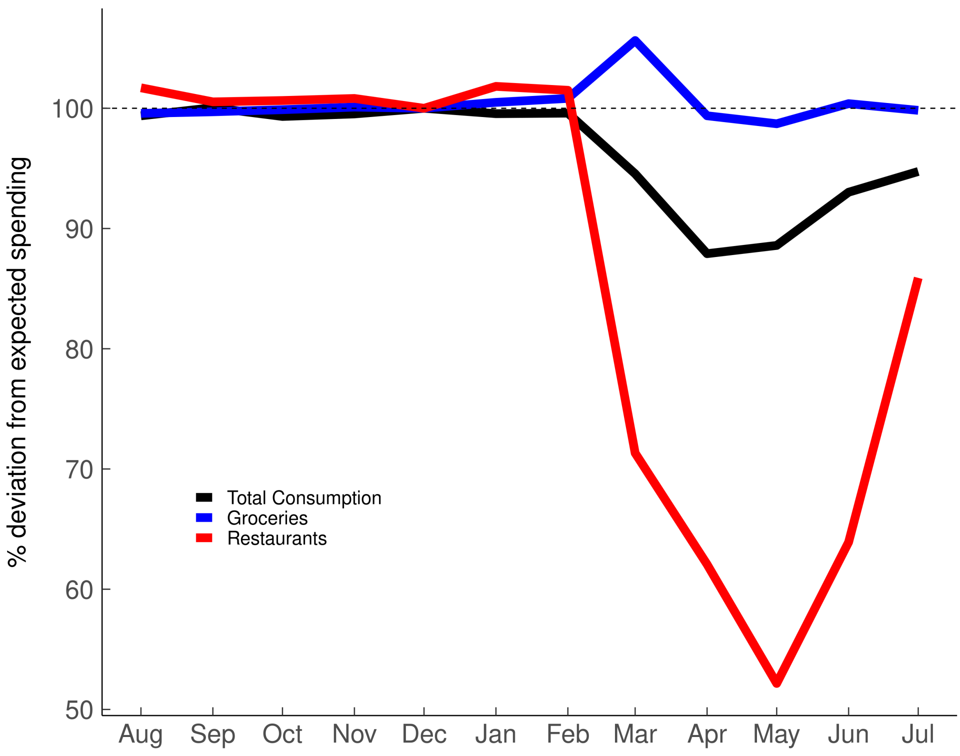


Figure 1: Comparing two different consumption sectors in Sweden.

to demonstrating against some cause together in the streets rather than sending petitions per e-mail. Viewed from that perspective, infection is inexorably linked to consumption or work place interaction, and we shall assume as much in our analysis.

We estimate a subset of the model parameters on Swedish weekly data on deaths for 2020. To preview our results, Figure 2 displays both the data from Sweden as well as from our estimated model and the SIR model with no interaction between the health and consumption dynamics. It shows that our model delivers a health dynamic that captures the empirical record in Sweden well, both the initially small number of death, its explosion during the month of March, and then the slower decline in May and June. Importantly, for the same initial conditions a pure epidemiological model predicts a quicker rise in deaths in March, but a slower pace. The reason that our epidemiological-economic model predicts a slower rise is that early in the pandemic, when words gets out that Covid-19 is a highly infectious disease that spreads differently through various consumption activities, individually rational households will both reduce consumption and labor input (as already pointed out by ERT), but crucially also substitute away from the most infectious activities. As a result, the onset of the pandemic is delayed, but once it starts and households have already adjusted towards less contagious consumption activities, it develops rapidly in the later weeks of March and early April.

Somewhat remarkable, the model not only captures well the health dynamics in Sweden, but pre-

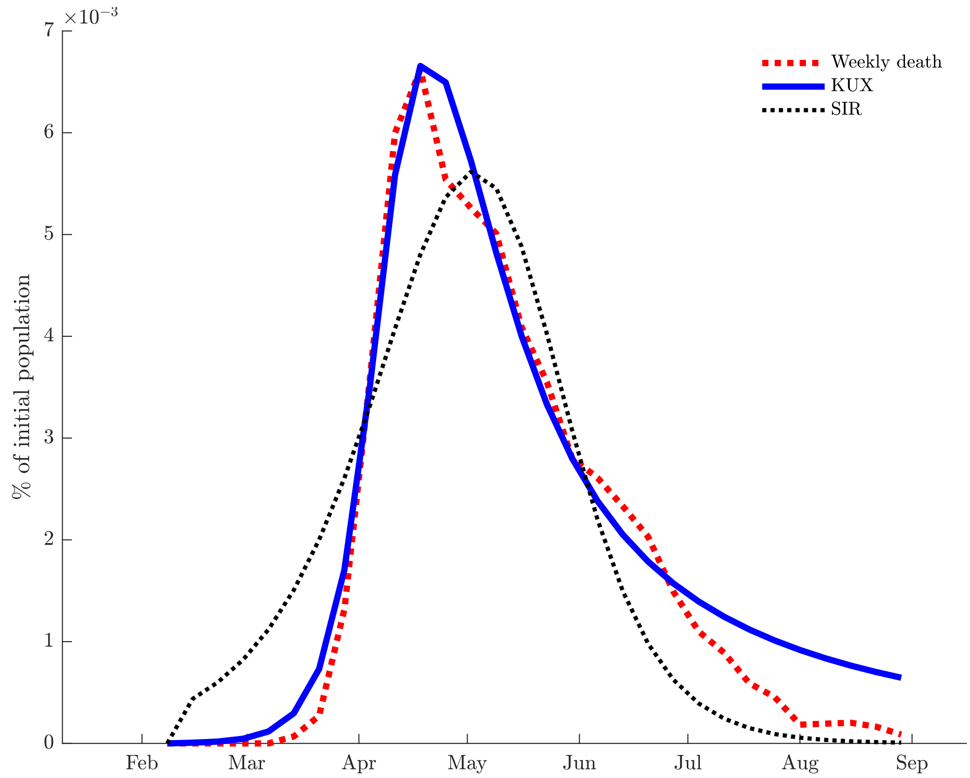


Figure 2: Comparison of optimised models. **Updated!**

dicts fairly accurately the size of the economic crisis induced by the pandemic. In the data aggregate consumption falls by ca. 10% in the second quarter of 2020. Our benchmark model predicts a decline of about 8% in measured consumption. Importantly, in the absence of sectoral reallocation the model would predict a collapse in measured consumption of about 23%, again demonstrating how potent the sectoral reallocation mechanism is for mitigating the health-induced economic crisis.

Our results are stark, partially because our analysis assumes smoothly functioning labor markets where workers can quickly reallocate to the sectors now in demand: waiters at restaurants deliver food instead, for example. It is easy to argue that the world is not as frictionless as assumed here and that the message of our paper is perhaps a bit too Panglossian. We do not wish to argue that the substantial mitigation happens as easily on its own. The analysis here does show, however, that recognition of substitution possibilities and recognition of private incentives of agents to become infected is potentially an important aspect in thinking about the current pandemic, both its onset but also its evolution as the economy is again opened to activity following the lock-down implemented in many countries.

Our analysis relates to other recent work that has emphasized the need to think about a multisector economy for the purpose of analyzing the economic effect of the recent epidemic, such as Alvarez et al. (2020), Glover et al. (2020), Guerrieri et al. (2020) or Kaplan et al. (2020). However, these authors do not feature the feedback from the differential infection probabilities across sectors into the private reallocation decision making of agents. A second very active literature evaluates the impact of publicly enforced mobility restrictions and social distancing measures on the dynamics of an epidemic, see e.g. Correia et al. (2020), Fang et al. (2020) or Greenstone and Nigam (2020). Complementary to this work we emphasize that private incentives to redirect consumption behavior might go a long way towards mitigating or even averting the epidemic, even in the absence of mobility restrictions or publicly enforced social distancing measures. Our paper complements the work by Barrero et al. (2020a) or, in shortened form, as Barrero et al. (2020b), who document that the covid-19 crisis is also a reallocation shock, when examining data for the U.S. economy. For the U.S., however, these sectoral reallocations may have mainly been driven by governmental restrictions. By contrast, our reallocation results from private concerns about infection risks only.

This paper is meant to clarify the key forces, rather than painting a completely accurate quantitative picture of the Swedish time series. We therefore focus first, in the model developed in section 2, on the infection risk in the consumption sector only. In section 3 we provide theoretical results that demonstrate the importance of the elasticity of substitution across sectors, and also argue that the same mechanism is at work if the risk of infections is located in the labor market rather than the consumption goods market, though one may wish to argue that the relevant elasticity of substitution is lower in that case. In section 4 set up the problem of a social planner who can observe which agents are infected and which are not, akin to the planning problem studied by Alvarez et al. (2020) One may think of this as a strong government with wide testing capabilities[1] of individuals, or a sufficiently powerful appeal to in particular the infected agents to do what is good for the country. Section 5 discusses the computation, calibration and estimation of the model, and the results for the baseline economy are contained in section 6, showing how individually rational reallocation of economic activity across sectors is a strong mitigating force of the crisis even in the absence of explicit government intervention. Section 7 conducts sensitivity analysis and section 8 contrasts the outcomes of the laissez-faire economy with that chosen by the social planner, arguing that the social planner can stop the pandemic in its tracks early and quickly. This should not be all that surprising: the social planner simply prevents infected agents from co-mingling with the susceptible part of the population (by separating consumption of both groups across sectors), even if this imposes considerable, additional pain on the infected agents, which the social planner of course takes into account. What is more surprising, though, is that the decentralized solution with its substitution possibilities goes a long way towards the private economy achieving a similar outcome, relative to an economy where these substitution opportunities are absent.

[1] In this sense our social planner analysis is akin in spirit to the focus on testing in Berger et al. (2020).

2 Model

2.1 The macroeconomic environment

Our framework builds on Eichenbaum-Rebelo-Trabandt (2020) or ERT for short, and shares some key model components. Time is discrete, $t = 0, 1, 2, \ldots$, measuring weeks. There is a continuum $j \in [0, 1]$ of individuals, maximizing the objective function

$$U = \mathbf{E_0} \sum_{t=0}^{\infty} \beta^t u(c_t^j, n_t^j)$$

where β denotes the discount factor, c_t^j denotes consumption of agent j and n_t^j denotes hours worked, and where expectations $\mathbf{E_0}$ are taken with respect to stochastic health transitions describe delow in detail. Like ERT, we assume that preferences are given by

$$u(c, n) = \ln c - \theta \frac{n^2}{2}$$

In contrast to ERT, we assume that consumption c_t^j takes the form of a bundle across a continuum of sectors $k \in [0, 1]$,

$$c_t^j = \left(\int (c_{tk}^j)^{1-1/\eta} dk \right)^{\eta/(\eta-1)} \tag{1}$$

where $\eta \geq 0$ denotes the elasticity of substitution across goods and c_{tk}^j is the consumption of individual j at date t of sector k goods. Workers can split their work across all sectors and earn a wage W_t in units of a numeraire good[2] for a unit of labor, regardless where they work. As the choice of the numeraire is arbitrary, we let a unit of labor denote that numeraire: thus, wages are equal to unity, $W_t = 1$.

Goods of sector k are priced at P_{tk} in terms of the numeraire, i.e. in units of labor. We suppose that production of goods in sector k is linear in labor, i.e. total output of goods in sector k equals the total number of hours worked there times some aggregate productivity factor A, and that pricing in each sector is competitive. Thus, prices equal marginal costs and are the same across all sectors,

$$P_{tk} = P_t = 1/A$$

[2]The presentation of the model is easier assuming a numeraire rather than payment in a bundle of consumption goods. We will not examine sticky prices or sticky wages in this model.

The date-t budget constraint of the household is therefore[3]

$$\int c_{tk}^{j} dk = A n_t^j \tag{2}$$

2.2 The epidemic

As in ERT, we assume that the population will be divided into four groups: the "susceptible" people of mass S_t, who are not immune and may still contract the disease but are not currently infected, the "infected" people of mass I_t, the "recovered" people of mass R_t and the dead of mass D_t. We assume that the risk of becoming infected, and the rate of death or recovery do not depend on the sector of work, but exclusively depend on consumption interactions. Our focus here is on the sectoral shift in consumption: for simplicity and in contrast to ERT, we assume that infected individuals continue to work at full productivity, but that the disease can only spread due to interacting consumers. We show in subsection 3.3, that this is similar to a model, where the infection can only spread via the workplace. In our robustness analysis, we also allow for the additional, purely mechanical possibility of autonomous transmissions from infected to susceptible individuals, regardless of their choices.

Different goods or, perhaps better, different ways of consuming rather similar goods differ in the contagiousness. To that end, we assume that there is an increasing function $\phi : [0, 1] \to [0, 1]$, where $\phi(k)$ measures the degree of social interaction or relative contagiousness of consumption in sector k (or variety k of a consumption good). We normalize this function to integrate to unity,

$$\int \phi(k) dk = 1 \tag{3}$$

Consider an agent j, who is still "susceptible": we denote this agent therefore with "s" rather than j. This agent is consuming the bundle $(c_{tk}^s)_{k\in[0,1]}$ at date t. Symmetrically, let $(c_{tk}^i)_{k\in[0,1]}$ denote the consumption bundle of infected people. Extending ERT, we assume that the probability τ_t^s for an agent of type s to become infected depends on his own consumption bundle, on the total mass of infected people and their consumption choices, and the degree $\phi(k)$ to which infection can be spread per unit of consumption in sector k,

$$\tau_t = \pi_s I_t \int \phi(k) c_{tk}^s c_{tk}^i dk + \pi_a I_t, \tag{4}$$

where π_s is a parameter for the social-interaction infection risk. For the robustness exercise later on, we have also included the autonomous infection risk parameter π_a. With (4), the total number of newly

[3]Different from ERT, we do not feature a tax-like general consumption discouragement and thus no government transfers. We also abstract from capital and thus from intertemporal savings decisions, at they do.

infected people is given by

$$T_t = \tau_t S_t \tag{5}$$

The dynamics of the four groups now evolves as in a standard SIR epidemiological model,

$$\begin{aligned} S_{t+1} &= S_t - T_t && (6)\\ I_{t+1} &= I_t + T_t - (\pi_r + \pi_d) I_t && (7)\\ R_{t+1} &= R_t + \pi_r I_t && (8)\\ D_{t+1} &= D_t + \pi_d I_t && (9)\\ \text{Pop}_{t+1} &= \text{Pop}_t - D_t && (10) \end{aligned}$$

where π_r is the recovery rate and π_d is the death rate, and where Pop_t denotes the mass of the total population at date t. As in ERT, we assume that the epidemic starts from initial conditions $I_0 = \epsilon$ and $S_0 = 1 - \epsilon$, as well as $R_0 = D_0 = 0$.

2.3 Choices

We proceed to analyze the choices of the individuals.

Susceptible people: Denote as $U_t^s(U_t^i)$ the lifetime utility, from period t on, of a currently susceptible (infected) individual. As in ERT, the lifetime utility U_t^s follows the recursion

$$U_t^s = u(c_t^s, n_t^s) + \beta[(1 - \tau_t)U_{t+1}^s + \tau_t U_{t+1}^i] \tag{11}$$

where the probability τ_t is given in equation (4) and depends on the choice of the consumption bundle $(c_{tk}^s)_{k\in[0,1]}$. An s-person maximizes the right hand side of (11) subject to the budget constraint (2) and the infection probability constraint (4), by choosing labor n_t^s, the consumption bundle $(c_{tk}^s)_{k\in[0,1]}$ and the infection probability τ_t.

The first-order condition for consumption of c_{tk}^s is

$$u_1(c_t^s, n_t^s) \cdot \left(\frac{c_t^s}{c_{tk}^s}\right)^{1/\eta} = \lambda_{bt}^s + \lambda_{\tau t}\pi_s I_t \phi(k) c_{tk}^i \tag{12}$$

where λ_{bt}^s and $\lambda_{\tau t}$ are the Lagrange multipliers associated with the constraints (2) and (4). This equation can be rewritten as

$$u_1(c_t^s, n_t^s) \cdot \left(\frac{c_t^s}{c_{tk}^s}\right)^{1/\eta} = \lambda_{bt}^s + \nu_t \phi(k) c_{tk}^i \tag{13}$$

where

$$\nu_t = \pi_s I_t \lambda_{\tau t} \tag{14}$$

Equation (13) reveals, that the risk of becoming infected induces an additional goods-specific component, scaled with the aggregate multiplicator ν_t, compared to the usual first order conditions for Dixit-Stiglitz consumption aggregators (at constant prices across goods). In the absence of the impact of consumption on infection $\lambda_{rt} = \nu_t = 0$ and there is no consumption heterogeneity across sectors, $c_{tk}^s = c_t^s$ for all k, as in the standard model. In the presence of this effect, then susceptible households shift their consumption to sectors with low risk of infection (i.e. those with a low $\phi(k)c_{tk}^i$).

Taking the consumption profile of infected households (c_{tk}^i) as given, by choosing her consumption portfolio a susceptible individual effectively chooses her infection probability τ_t. As in ERT, the first-order condition for τ_t reads as

$$\beta(U_{t+1}^s - U_{t+1}^i) = \lambda_{\tau t} \tag{15}$$

The first-order condition with respect to labor is completely standard and reads as

$$u_2(c_t^s, n_t^s) + A\lambda_{bt}^s = 0 \tag{16}$$

Note that we have excluded the workplace infection, in contrast to ERT. We examine this possibility in subsection 3.3 below. With the chosen utility function, this first order condition simplifies to:

$$\theta n_t^s = A\lambda_{bt}^s \tag{17}$$

Infected people and recovered people: As in ERT, the lifetime utility of an infected person is

$$U_t^i = u(c_t^i, n_t^i) + \beta[(1 - \pi_r - \pi_d)U_{t+1}^i + \pi_r U_{t+1}^r + \pi_d \times 0] \tag{18}$$

Taking first order conditions with respect to the consumption choices and labor results in

$$u_1(c_t^s, n_t^s) \cdot \left(\frac{c_t^i}{c_{tk}^i}\right)^{1/\eta} = \lambda_{bt}^i, \tag{19}$$

where λ_{bt}^i is the Lagrange multiplier on (2) for an infected person. This is the usual Dixit-Stiglitz CES first order condition at constant prices, with solution

$$c_{tk}^i \equiv c_t^i \tag{20}$$

That is, as long as $\eta \in (0, \infty)$, infected individuals find it optimal to spread their consumption evenly across sectors, given that all sector goods have the same price, are imperfect substitutes, and differential infection probabilities across sectors are irrelevant for already infected individuals. Exploiting this result and the specific form of the period utility function (which implies $u_1(c, n) = 1/c$) in equation (19) yields $1/c_t^i = \lambda_{bt}^i$. For labor, we obtain the standard first order condition

$$\theta n_t^i = A\lambda_{bt}^i = \frac{A}{c_t^i} \tag{21}$$

Finally, exploiting the budget constraint (2), we arrive at the equilibrium allocations for infected people given by

$$n_t^i = \frac{1}{\sqrt{\theta}}, \; c_t^i = \frac{A}{\sqrt{\theta}} \tag{22}$$

Likewise, the lifetime utility for a recovered person is

$$U_t^r = u(c_t^r, n_t^r) + \beta U_{t+1}^r \tag{23}$$

Given our assumptions, the optimal decision for both the i group and r group is the same[4]: we will therefore use c_t^i, $c_{t,k}^i$, n_t^i and λ_{bt}^i to also denote the choices of recovered individuals.

[4]Note here that we implicitly assume that infected people will be fully at work. One might alternatively wish to assume that only a fraction of them are at work instead. Given our assumptions about excluding infections in the work place, this does not affect the infection rate via that channel. However, lowering the amount of income of infected people lowers their consumption and thus lowers their ability to infect others in the consumption market. We do not wish to emphasize this channel, though: in a somewhat richer model, people will have a buffer stock of savings, and an infected person would then draw on these savings to finance consumption rather than respond to the temporary decline in labor income. Alternatively, income may fall considerably less in practice than the model would otherwise imply here, due to various social insurance policies.

2.4 Equilibrium Characterization

In equilibrium, each individual solves her or his maximization problem, and the labor and goods market has to clear in every period. Let n_{tk} be total labor employed in sector k. The market clearing conditions then read as:

$$\begin{aligned} S_t c^s_{tk} + (I_t + R_t) c^i_{tk} &= A n_{tk} && (24) \\ \int n_{tk} dk &= S_t n^s_t + (I_t + R_t) n^i_t && (25) \end{aligned}$$

Given the solution to the problem of infected and recovered people, this can be simplified to

$$\begin{aligned} S_t c^s_{tk} + (I_t + R_t) \frac{A}{\sqrt{\theta}} &= A n_{tk} \\ \int n_{tk} dk &= S_t n^s_t + (I_t + R_t) \frac{1}{\sqrt{\theta}} \end{aligned}$$

The equations can be simplified further to a set of aggregate variables as well as an equation determining the sectoral allocation, see appendix section B.

3 Theoretical Results

3.1 The Value of a Statistical Life

The calculations above allow us to calculate the implied value of a statistical life or VSL, using the following thought experiment. Suppose that there is no epidemic, but that an agent may be exposed to some small probability $\delta > 0$ of not surviving to the next period. How much would current consumption have to be increased, in order to compensate the agent for this additional risk? That is, when would the agent be indifferent between a riskless scenario and the scenario of taking this risk plus the compensation per increassed current consumption?

Without the epidemic, the consumption of all agents is given by (22) or

$$c^* = \frac{A}{\sqrt{\theta}} \text{ and } n^* = \frac{1}{\sqrt{\theta}},$$

implying current utility and lifetime utility

$$u^* = \log\left(\frac{A}{\sqrt{\theta}}\right) - \frac{1}{2} \text{ and } U^* = \frac{u^*}{1-\beta} u^*$$

In the riskless scenario, the agent receives lifetime utility

$$U^* = u^* + \beta U^*$$

In the risky scenario, the agent receives expected lifetime utility

$$\log\left(e^{\gamma}\frac{A}{\sqrt{\theta}}\right) - \frac{1}{2} + (1-\delta)\beta U^*$$

where γ is the compensating increase of current consumption, expressed in percent (and divided by 100). Equating these two expressions, solving for γ and with the value of a statistical life expressed as the percent increase in the consumption of one period required to compensate for the a one percent increase in the death probability,

$$\text{VSL} := \frac{\gamma}{\delta}, \tag{26}$$

we find

$$\text{VSL} = \frac{\beta}{1-\beta}\left(\log\left(\frac{A}{\sqrt{\theta}}\right) - \frac{1}{2}\right) \tag{27}$$

One now needs to keep in mind that the length of period matters: that percentage increase would need to be four times as large, when calculated for weekly rather than monthly consumption, for example. To calculate the actual value of a statistical life in Dollar, say, one therefore needs to multiply VSL with the Dollar amount of consumption of one period.

With the epidemic as described in the model, one can thus think of susceptible agents to think about reducing the current consumption aggregate by VSL percent, if this allows them to increase their survival chances by one perecent for next period: the larger VSL, the more the agent is willing to endure a reduction in consumption. It is this trade-off that gives rise to the implied consumption dynamics in our model. Equation (27) shows, that these calculations regarding the value of a statistical value of life depend on the preference and productivity parameters via β as well as the ratio $A/\sqrt{\theta}$ or steady state consumption c^*. Furthermore, (27) shows, that this value can be negative in principle, if $A/\sqrt{\theta}$ is smaller than $\exp(0.5) \approx 1.65$. We will avoid that in our parameterization, as it would imply a desire for agents to die.

3.2 Two extreme values of the elasticity of substitution η

It is instructive to consider extreme values for the elasticity of substitution η. The first extreme is an elasticity of substitution of zero such that the consumption aggregator is of the Leontieff form.

Proposition 1. *Suppose that $\eta = 0$, i.e. that the consumption aggregation in (1) is Leontieff. In that case, the multisector economy is equivalent to a multisector economy with a ϕ-function, which is constant and equal to 1,*

Proof. With Leontieff consumption aggregation, consumption is sector independent, $c^j_{tk} \equiv c^j_t$. Equations (4) and (5) now become

$$\tau_t = \pi_s I_t \int \phi(k) c^s_t c^i_t dk = \pi_s I_t c^s_t c^i_t \int \phi(k) dk = \pi_s I_t c^s_t c^i_t \tag{28}$$

and

$$T_t = \pi_s S_t I_t \int \phi(k) c^s_{tk} c^i_{tk} dk = \pi_s S_t I_t c^s_t c^i_t \tag{29}$$

□

Equations (28) and (29) furthermore show, that the Leontieff version is equivalent to the one-sector economy in ERT. The other extreme is the case where goods are perfect substitutes.

Proposition 2. *Suppose that $\eta \to \infty$, i.e. that the sector-level consumption goods in (1) are perfect substitutes in the limit, Let $\underline{k} = \sup_k \{k \mid \phi(k) = \phi(0)\}$. Assume that $\underline{k} > 0$, i.e. that there is a nonzero mass of sectors with the lowest level of infection interaction. Suppose that $I_0 > 0$. Then there is a limit consumption c^j_{tk} for $j \in \{s, i, r\}$ as $\eta \to \infty$, satisfying*

$$c^s_{tk} = \begin{cases} c^s_t / \underline{k} & \text{for } k < \underline{k} \\ 0 & \text{for } k > \underline{k} \end{cases} \tag{30}$$

and

$$c^j_{tk} \equiv c^j_t \text{ for } j \in \{i, r\} \tag{31}$$

Equations (4) and (5) are replaced by

$$\tau_t = \pi_s \phi(0) I_t c^s_t c^i_t \tag{32}$$

and

$$T_t = \pi_s \phi(0) S_t I_t c_t^s c_t^i \tag{33}$$

That is, susceptible individuals only consume in the lowest infection-prone sectors with $\phi(k) = \phi(0)$, and infected (as well as recovered) individuals consume uniformly across all sectors.

Proof. Equation (31) is just equation (20), which also holds for recovered agents: it will therefore also hold, when taking[5] the limit $\eta \to \infty$. Equation (30) follows from (14) together with (1), taking $\eta \to \infty$. Define the consumption distribution of type $j \in \{s, i, r\}$ as $\kappa_t^j(k) = c_{tk}^j / c_t^j$ and note that

$$\int \kappa_t^j(k) dk = 1 \tag{34}$$

and that

$$\kappa_t^j(k) \geq 0, \text{ all } k \tag{35}$$

Rewrite (4) and (5) as

$$\tau_t = \pi_s I_t c_t^s c_t^i \int \phi(k) \kappa_t^s(k) \kappa_t^i(k) dk \tag{36}$$

Therefore and analogously to ERT, the total number of newly infected people is given by

$$T_t = \pi_s S_t I_t \int \phi(k) \kappa_t^s(k) \kappa_t^i(k) dk \tag{37}$$

Equations (32) and (33) now follow from observing that $\kappa_t^i(k) \equiv 1$ and $\kappa_t^s(k) = 1/\underline{k}$ for $k \in [0, \underline{k}]$ and zero elsewhere as well as noting that $\phi(k) = \phi(0)$ for $k \in [0, \underline{k}]$. $\square$

The result of this proposition is depicted in figure 3. Equations (32) and (33) also show, that the limit is equivalent to the one-sector economy in ERT, with π_s replaced by $\pi_s \phi(0)$. Infection only takes place in the sector with lowest infection hazard, thus introducing the extra factor $\phi(0)$. The size of the sector, however, does not enter. With a smaller size of that sector and with equal distribution of infected agents across all sectors, susceptible agents meet a smaller fraction of infected agents in that sector on the one hand, a mitigating force. On the other hand, the consumption activity of susceptible agents in these sectors rises, an enhancing force. These two exactly cancel. Given that the size of the sector

[5]Note that it does not necessarily hold **at** the limit, as infected and recovered agents there are indifferent as to which goods to consume

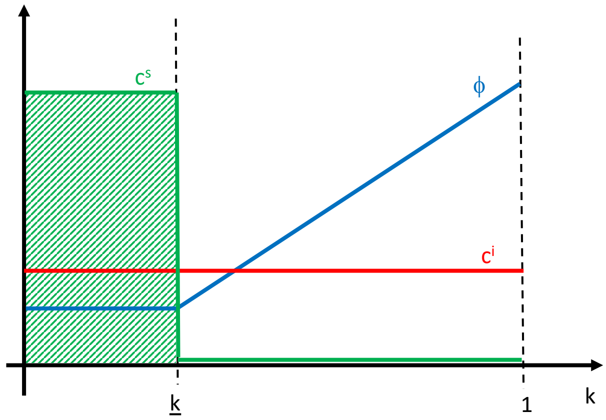


Figure 3: When $\eta \to \infty$.

with lowest infection hazard does not matter at both extreme ends given in propositions 1 and 2, one might conjecture that it is never relevant. However, numerical simulations indicate, that larger rates of infection occur if that sector is smaller, for substitution elasticies $0 < \eta < \infty$.

Proposition 2 above exploits the fact that infected agents wish to spread their consumption equally across all sectors for any finite value of η. At the limit $\eta = \infty$, infected agents are entirely indifferent, though. At the one extreme, they might consume rather large portions of the low-k goods. At the other extreme, they stick to each other in the high-infection-risk segments, and not consume the low-k-goods at all. In that latter case, the infection probabilities become zero and the spread of the disease is stopped entirely. The following proposition provides the resulting range for the infection probabilities.

Proposition 3. *Suppose that $\eta = \infty$, i.e. that the sector-level consumption goods in (1) are perfect substitutes. Let μ_t be any function of time satisfying*

$$0 \leq \mu_t \leq \bar{\mu}$$

where $\bar{\mu}$ is defined as

$$\bar{\mu} = \frac{1}{\int \frac{1}{\phi(k)} dk} \tag{38}$$

and note that it satisfies

$$\phi(0) \leq \bar{\mu} \leq 1 \tag{39}$$

Then there is an equilibrium with equations (4) and (5) replaced by

$$\tau_t = \pi_s \mu_t I_t c_t^s c_t^i \tag{40}$$

and

$$T_t = \pi_s \mu_t S_t I_t c_t^s c_t^i \tag{41}$$

Proof. We first show (39). For the lower bound, note that

$$\int \frac{1}{\phi(k)} \leq \int \frac{1}{\phi(0)} = \frac{1}{\phi(0)}$$

The upper bound follows from Jensen's inequality and (3). We next shall show, that there is an equilibrium, when μ_t equals one of the two bounds. Given the consumption distribution function κ_t^i, note that the problem of the susceptible agents is to choose their own consumption distribution function κ_t^s so as to minimize (36), subject to the constraints (34) and (35). The Kuhn-Tucker first order condition imply that $\kappa_t^s(k) = 0$, unless

$$k \in \{k \mid \phi(k)\kappa_t^i(k) = \min \phi(k)\kappa_t^i(k)\}$$

For $\mu_t = 0$, let infected agents consume zero, $\kappa_t^i(k) = 0$ for all k in some subset $\mathcal{K}$ of $[0, 1]$. In that case and per the argument just provided, susceptible people choose $\kappa_t^s(k) > 0$ only if $k \in \mathcal{K}$. Conversely, the worst case scenario in terms of infection arises, if $\phi(k)\kappa_t^i(k)$ is constant. Given (34), this yields

$$\kappa_t^i(k) = \frac{\bar{\mu}}{\phi(k)} \tag{42}$$

Given this κ_t^i function, susceptible agents are now indifferent in their consumption choice. Any κ_t^s function satisfying (34) and (35) then results in

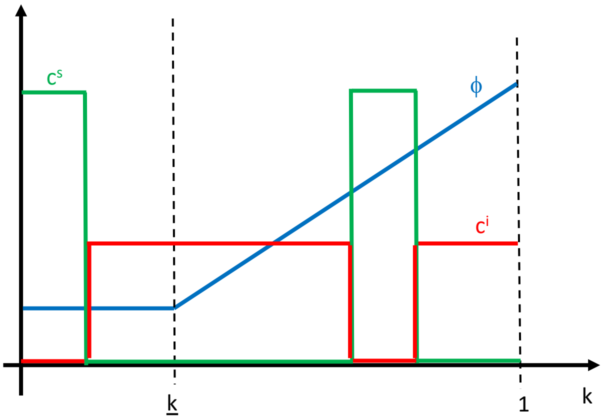
$$\int \kappa_t^s \phi(k)\kappa_t^i(k)dk = \bar{\mu}$$

and thus (40) and (41) at $\mu_t = \bar{\mu}$, i.e. the upper bound. Finally, let $0 < \mu_t < \bar{\mu}$ and let $\lambda = \mu_t/\bar{\mu}$. Let $\mathcal{K}$ be a measurable subset of $[0, 1]$ with mass strictly between 0 and 1. Set

$$\kappa_t^i(k) = \begin{cases} \lambda \frac{\bar{\mu}}{\phi(k)}, & \text{for } k \in \mathcal{K} \\ \tilde{\lambda} \frac{\bar{\mu}}{\phi(k)}, & \text{for } k \in [0, 1] \backslash \mathcal{K} \end{cases}$$

where $\tilde{\lambda}$ is chosen such that (34) holds. Then, susceptible agents will choose $\kappa_t^s(k) = 0$ for all $k \in [0,1]\backslash\mathcal{K}$, are indifferent between $k \in \mathcal{K}$, and (40) and (41) hold true for the chosen μ_t. □

Best case scenario:



Worst case scenario:

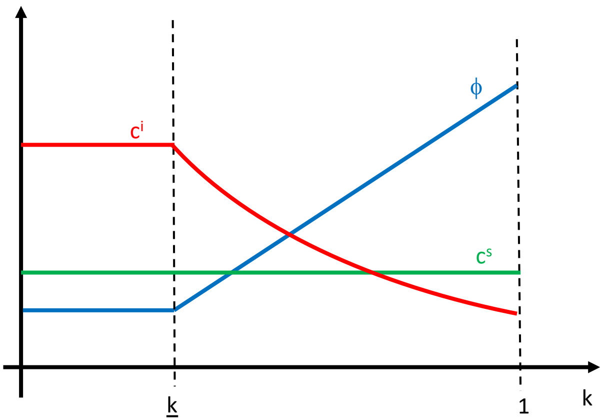


Figure 4: When $\eta = \infty$.

The result of this proposition is depicted in figure 4. The top graph depicts the best-case scenario, when susceptible and infected agents consume entirely different bundles of goods. The bottom graph depicts the worst-case scenario, when $\phi(k)\hat{\c{}}i(k)$ is constant: in that case, a constant $c^s(k)$ is the best solution for susceptible agents under these circumstances. That bottom graph and the proposition show, that the perfect substitutability might be nearly as bad as the Leontieff case, if infected people behave particularly badly and distribute their consumption according to (42). Equations (40) and (41) are then the same equations as in the ERT model with π_s replaced by $\pi_s\bar{\mu}$. On the other hand, perfect substitutability can also result in the most benign scenario of a zero spread of consumption, if infected and susceptible people simply consume different goods.

There are fascinating policy lessons in here. Given that infected people will end up seeking services and consumption, it might be best to encourage them to seek out those types, where the degree of interaction is high, rather than forcing all agents, including the infected agents, into the low infection transmission segments. The model here shows that this can have dramatic consequences for the spread of the disease.

3.3 Infections in the Labor Market

Thus far we have assumed that infections can take place when acquiring consumption goods. We could have similarly allowed for heterogeneity in labor and assumed that it is at work in the labor market where individuals face the risk of contracting the virus. We explore this possibility in this section, offering two alternative approaches, and shall show that the formal analysis is conceptually similar and, for the first approach, actually equivalent to the model analyzed above. In economic terms and interpretation, the key distinction is arguably less in the formal differences between both versions of the model, but rather in the empirically plausible choice for the elasticity of substitution η: while it may be possible to easily substitute between different types of similar consumption goods ("Pizza at home" versus "Pizza in a restaurant"), the same may not be true for work (restaurants will still have to produce the to-be-delivered pizza in the restaurant kitchen, rather than having their workers stay at home and produce in their own kitchens). Our results for the lower elasticity of substitution $\eta = 3$ may thus be more appropriate for the analysis of infection-at-the-work-place. In the extreme without substitution possibilities, we are back at the homogeneous sector case.

As for the formal analysis, maintain the assumption that the period utility function is given by

$$u(c, n) = \log(c) - \theta \frac{n^2}{2} \tag{43}$$

but now assume that consumption c is a homogeneous good, while household labor n is a composite of differentiated sector-specific labor n_k, $k \in [0, 1]$. For the first, production-based approach to aggregation, assume that labor supplied by the household to the market is a CES composite of sector-specific labor, i.e. that $n = \int n_k dk$ as far as preferences are concerned, but that the budget constraint reads

$$c = A \left(\int n_k^{1-(1/\alpha)} dk \right)^{\alpha/(\alpha-1} \tag{44}$$

Assume now, that infections occur in the labor market instead of per joint consumption, i.e. assume that the probability of a susceptible individual to become infected is given by

$$\tau_t = \tilde{\pi}_s I_t \int \phi(k) n^i_{tk} n^s_{tk} dk + \pi_a I_t \tag{45}$$

In Appendix C we establish the following result.

Proposition 4. *Suppose that $\tilde{\pi}_s = A^2 \pi_s$ and that $\alpha = \eta$. In that case, the production-based labor aggregation with infection in the labor market is equivalent to the consumption-infection economy described above, i.e. all aggregates remain the same, while $n^s_{tk}/n^s_t = c^s_{tk}/c^s_t$, when comparing the ratio of sector-specific labor to the labor aggregate in the labor-market-infection economy to the ratio of sector-specific constumption to the consumption aggregate in the consumption-infection economy.*

For this formal equivalence, it is important that the aggregation (44) takes place at the household level and not at the firm level, i.e. in firms hiring labor from different households. The latter would provide an interesting alternative environment for studying the sectoral shift issues raised here, but requires additional restrictions to preclude complete separation of infected and susceptible agents in equilibrium.

The household-level labor aggregation described above may be be hard to envision as an environment for sector-specific contagion risk. We therefore offer a second, preference-based approach. For that, think of the household as composed of individual workers, each specialized to work in sector k, and that total household leisure, described by $\ell = f(n)$ for some strictly decreasing and differentiable function[6] f is a CES-aggregate of worker-specific leisure,

$$f(n) = \left(\int f(n_k)^{1-1/\alpha} dk \right)^{\alpha/(\alpha-1)} \tag{46}$$

for some elasticity of substitution $\alpha \geq 0$. The household budget constraint is $c = A \int n_k dk$. The probability of infection is given by (45). This economy shares the the same basic forces as the heterogeneous consumption sector economy, although its analysis it is not exactly equivalent. In Appendix C we demonstrate this more formally. The remarks here are simply meant to show that the mechanisms in both types of labor-infection-based models are rather similar to our baseline consumption-based-infection economy indeed. We therefore skip a full quantitative analysis and do not to integrate this feature into the ensuing analysis.

[6] Useful specifications are $f(n) = \bar{L} - n$ for some time endowment $\bar{L}$ or $f(n) = 1/n$.

4 Social Planning Problem

It is instructive to compare our results to that of a social planner with the ability to test individuals, i.e. with full knowledge of who is susceptible, infected or recovered. However, in the same way the agents in our model the planner cannot separate the infected from the susceptible (and recovered), when they consume (that is, the planner cannot change the consumption technology). Therefore, as in the decentralized economy, the spread of the disease while consuming can at best be mitigated by allocating consumers to low-infectious sectors. The social planner maximizes date-0 aggregate social welfare W_0, where

$$W_0 = \sum_{t=0}^{\infty} \beta^t \left[S_t u\left(c_t^s, n_t^s\right) + I_t u\left(c_t^i, n_t^i\right) + R_t u\left(c_t^r, n_t^r\right) \right]$$

subject to the following constraints, and with the respective Lagrangian multipliers, after substituting out the infection risk for susceptible people, τ_t, and the number of newly infected people, T_t:

$$\mu_{f,t}: \qquad \int S_t c_{tk}^s + I_t c_{tk}^i + R_t c_{tk}^r dk = A\left(S_t n_t^s + I_t n_t^i + R_t n_t^r\right) \tag{47}$$

$$\mu_{S,t}: \qquad S_t = S_{t-1} - I_t + (1 - \pi_r - \pi_d) I_{t-1} \tag{48}$$

$$\mu_{I,t}: \quad I_t = \pi_s S_{t-1} I_{t-1} \int \phi(k) c_{t-1,k}^s c_{t-1,k}^i dk + (1 - \pi_r - \pi_d) I_{t-1} \tag{49}$$

$$\mu_{R,t}: \qquad R_t = R_{t-1} + \pi_r I_{t-1} \tag{50}$$

The social planner takes S_0, I_0 and R_0 as given. It chooses the time paths of consumptions for susceptible, infected and recovered people c_{kt}^x for $x \in \{s, i, r\}$, the path for labor supply $n_t^x, x \in \{s, i, r\}$, and the paths for the mass of agents in the four groups S_t, I_t, and R_t. The first order conditions of the social planner's problem are presented in Appendix D.

5 Computation, Calibration and Estimation

5.1 Computational Strategy

The unknowns to be carried around (aside from the sector-specific consumption): $U_t^s, c_t^s, n_t^s, \lambda_{bt}^s, \nu_t, \tau_t$. The equations determining these variables are the Bellman equation (11), the budget constraint (2), the infection constraint (B.8), the share constraint (B.5) replacing the original first order condition with respect to consumption, the first order condition with respect to labor (16) and the first order condition with respect to τ (15) combined with (14). One can easily eliminate λ_{bt} and n_t^s, using (2) and (16), as well as eliminate ν_t with (14) and (15): what remains then is a system in three unknowns U_t^s, c_t^s, τ_t and three equations, two of which are nonlinear integral equations, that would need to be solved. The way to proceed is from a distant horizon, and working backwards. Knowing U^s_{t+1} allows one to compute ν_t with (14) and (15). Using the two integral equations (having substituted out λ^s_{bt} and n^s_t) allows one to compute c^s_t and τ_t. From there compute n_t with (2) and U^s_t.

We use Dynare 4.6 to perform the calculations. The economy is hit by an MIT shock in ε, the initial infected population. A perfect foresight solution with 500 periods is first found by setting π_s to a very small value. At this value, the economy is close to one without a disease outbreak, making it easy for Dynare to find a solution. We then introduce a small increment to π_s, using the solution for the previous π_s value as the initial state. The initial state is updated once a solution at the new π_s value is found. This process is iterated until π_s reaches the desired value.

5.2 Calibration and Estimation

We mostly investigate a two-sector economy, where both sectors are of equal size, and sector 1 has infection intensity ϕ_1 satisfying $0 < \phi(k) = \phi_1 < 1$ for $k \in [0, 0.5]$. Given the maintained assumption that the average $\phi(k)$ is equal to one, this implies that $\phi_2 = 2 - \phi_1$ for $k \in (0.5, 1]$. We set $\eta = 3$ and as an alternative, $\eta = 10$ approaching the perfect substitutes case in Proposition 2. The ERT specification results for $\phi_1 = \phi_2 = 1$.

We choose the remaining parameters of our model in two steps. In a first step and for the "economics" side, we choose parameters in line with Eichenbaum et al. (2020) who employ a one-sector version of the model we use to study the joint dynamics of health and economic activity during the Covid-19 crisis in the U.S. We summarize the parameters fixed so far in table Table 1. Equation (27) can then be used to calculate the implied value of a statistical life as VSL = 8298, expressed as the percentage change in one-week consumption to compensate for a one-percent change in death probability. Weekly per-capita consumption in Sweden is about 500 U.S. Dollar. Multiplying this with VSL yields about 4 million U.S. Dollar as the value of a statistical life, expressed in U.S. Dollar. This strikes us in the ball park of numbers often used in practice. We therefore feel comfortable proceeding with this parameterization[7]

We next estimate the parameters governing the epidemic dynamics. The epidemiological parameters in our model, π_s, π_r, and π_d, govern the probabilities of infection, recovery, and death. The initial infected population determines the timing at which the infection curve soars. The π_r and π_d parameters are associated with the number of days for an infected case to recover or die, and the case fatality rate,

[7]The Dollar VSL may be a bit on the high side, given that we shall think of the agents in our model to be in "mid life", when they consider this remaining infinite-horizon VSL, when making their consumption choices.

Table 1: Economic Parameters.

Parameter	**Value**	**Description**
η	3.000	Elasticity of substitution
θ	1.275×10^{-3}	Labor supply parameter
A	39.835	Productivity
β	$0.96^{1/52}$	Discount factor
υ_1	0.500	Size of the low-interaction sector
υ_2	0.500	Size of the high-interaction sector

per the following equations (recall that our model is solved at weekly frequency):

$$\pi_r = (1 - \text{“case fatality rate”}) \times \frac{7}{\text{“days to recover or die”}} \tag{51}$$

and

$$\pi_d = \text{“case fatality rate”} \times \frac{7}{\text{“days to recover or die”}} \tag{52}$$

where the constant 7 corresponds to weekly statistics. We therefore search over values for the days to recover or die, the case fatality rate, the initial fraction ϵ of infected people as well as the infection risk parameter π_s to minimize the root mean square error (RMSE) between the simulated and actual weekly death counts between February and August 2020. For the number of days to recover or die, we restrict the range to $\{4, 7, 10, 14, 21\}$. For the case fatality rate, the range is $\{.05\%, .1\%, .15\%, .2\%\}$. For the initial infected population, the range is $\{10^{-5}, 5 \times 10^{-5}, 10^{-4}, 1.5 \times 10^{-4}, 2 \times 10^{-4}\}$. The range of infection probability π_s is restricted to $[10^{-7}, 3 \times 10^{-6}]$ with steps of 10^{-8}. The grid search is conducted for values of ϕ_1 from $\phi_1 = 0.1$ to $\phi_1 = 1$ with an increment of 0.1. The parameter values producing the best-fit weekly death dynamics for each ϕ_1 value is presented in Table 2. Given these best-fitting parameters, we calculate the values of π_r and π_d for our model. We also calculate the implied initial replication number R_0, i.e. the number of new infections per number of infected individuals at steady state consumption levels

$$R_0 = \frac{\pi_s \frac{A^2}{\theta} + \pi_a}{\pi_r + \pi_d} \tag{53}$$

The results is contained in Table 2. Given these parameters, we pick $\phi_1 = 0.2$ for our benchmark calibration since it minimizes the RMSE between the model and the data. Note that at this value for $\phi_1 = 0.2$, the model implies a relatively high initial R_0.

Note that the favored parameterizations for all models imply case fatality rates below 0.2 percent. In our dynamic calculations below, we furthermore find a limit of less than 800 death per million for

Table 2: Results from grid search

Model	ϕ_1	π_a	π_s $\times 10^{-6}$	Days to recover or die	Case fatality rate (per cent)	Initial infection ε	RMSE $(\times 10^{-4})$	π_r	π_d	R_0
SIR	-	2.2	0	3.8	.16	1.50E-03	8.49	1.529	.291	1.20
	.1	-	2.04	10	.10	5.00E-05	4.32	.699	.001	3.63
	.2	-	1.82	10	.10	1.00E-04	3.95	.699	.001	3.24
	.3	-	2.14	7	.10	5.00E-05	3.96	.999	.001	2.66
	.4	-	1.86	7	.10	1.50E-04	4.00	.999	.001	2.31
KUX	.5	-	2.54	4	.15	5.00E-05	4.70	1.747	.003	1.81
	.6	-	2.46	4	.15	5.00E-05	4.30	1.747	.003	1.75
	.7	-	2.30	4	.15	1.00E-04	3.98	1.747	.003	1.64
	.8	-	2.20	4	.15	1.50E-04	4.11	1.747	.003	1.56
	.9	-	2.18	4	.15	1.50E-04	4.70	1.747	.003	1.55
ERT	1.0	-	2.16	4	.15	1.50E-04	5.01	1.747	.003	1.54

Sweden, corresponding to this rather low case fatality rates. Here, one ought to keep in mind that the model does not allow for the possibility of a "second wave" or other time-varying features for the infection dynamics: thus, the shape of the weekly death dynamics data for Sweden exhibited in figure 2 allows the model no other conclusion, that Sweden is approaching herd immunity, i.e. is nearing the limit in the total death toll. Time will tell, whether this prediction will be borne out by future evidence.

6 Results for the Benchmark Economy

We now present our results, starting with the findings for our benchmark economy with two sectors which was calibrated to the Swedish health data as described above. To clarify the quantitative importance of our mechanism, we also contrast the results from the benchmark economy to that of a representative sector economy akin to the one used by ERT where by construction the sectoral reallocation channel is absent. In this section, in order to facilitate the comparison between both model variants we keep the health parameters fixed; the only difference is ϕ_1 which takes the value $\phi_1 = 0.2$ for our benchmark economy and $\phi_1 = 1$ for the representative sector economy.

Figure 5 displays the number of weekly deaths in the data as well as in the two versions of the model. It is identical to Figure 2 in the introduction, but replaces the death dynamics implied by the purely epidemiological SIR model with that predicted by the representative sector economy.

We observe that, as already documented in the introduction, the baseline model with sectoral allocation captures the death dynamics very well, especially early in the pandemic. As the comparison with the one-sector economy shows, economic adjustments of private agents are absolutely crucial for this result. Without private households relocating consumption activity to the less infectious sector, the disease explodes in April, with weekly deaths close to three times as large as in the sectoral reallocation

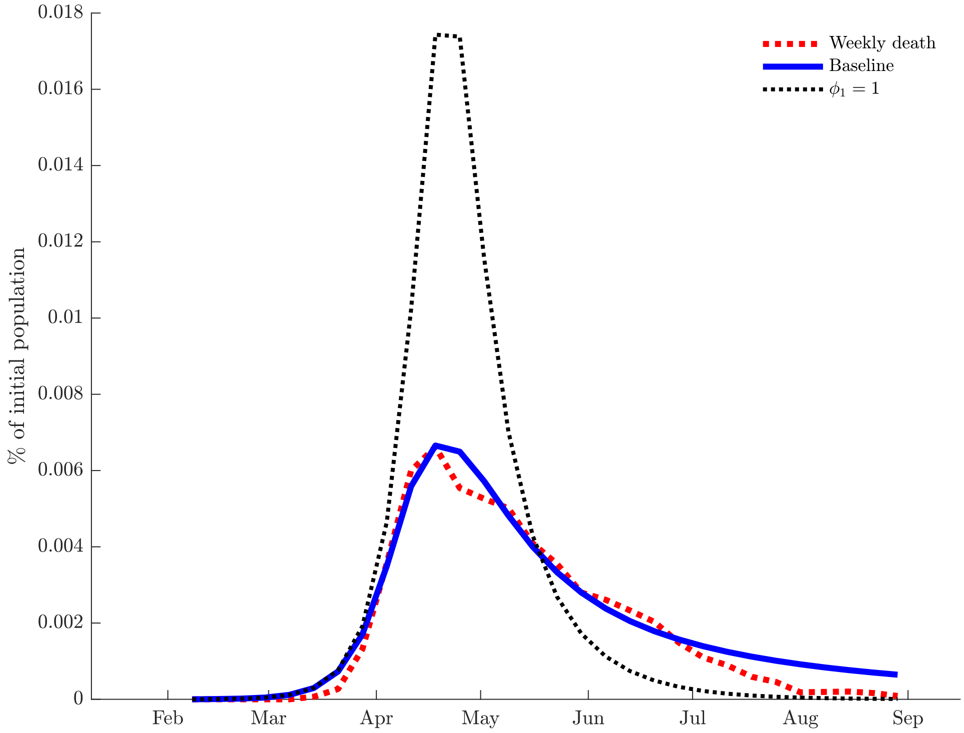


Figure 5: Weekly Deaths: Swedish Data and Models.

model (and the data).[8]

In Fig. 6 we display the health- and economic dynamic in our benchmark model (blue solid line) and contrast it with the economy in which our reallocation mechanism is absent since $\phi \equiv 1$ as in ERT (the doted black line). When the virus breaks out, susceptible households optimally substitute consumption goods from the high-infection sector with goods from the low-infection sector, while maintaining a relatively stable consumption path. Such a behaviour lowers the risk of being infected from participating in high-infection activities. As a result, the infection rate is only a fraction of that in a homogeneous-sector economy. Both the consumption decline and the number of deaths are considerably mitigated. The cumulative death figures show that the limit will be less than 800 death per million. Once again, one ought to keep in mind, that the mode does not allow for the possibility of a second wave or other complicating features.

In Fig. 7, we show the sectoral consumption dynamics underpinning the differences between the two model variants. As expected, due to households substituting goods from the high-infection sector with those from the low-infection sector, consumption in the low-infection sector experiences an increase, mitigating the decline in aggregate consumption, which falls by 15%. Note, however, that consumption

[8]This is not meant at all as a knock on the the original ERT model, since we estimated the parameters so that *our model* fits the health data. In section 7 we will document the disease dynamics implied by the homogeneous sector economy once we estimate this version of the model.

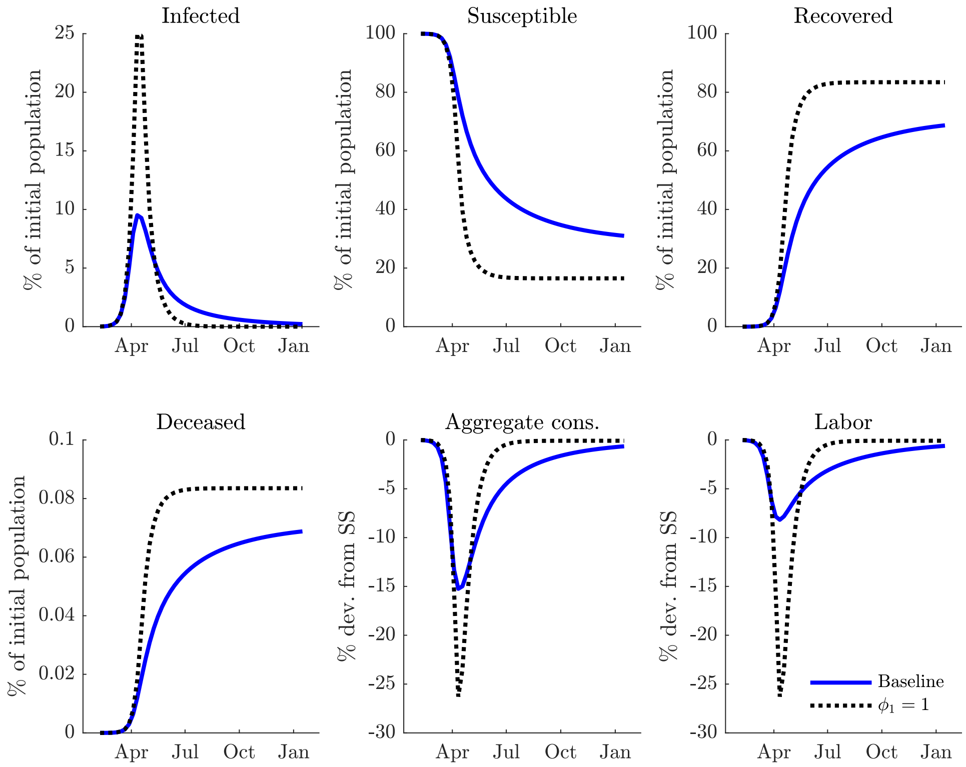


Figure 6: Comparison of our baseline model with a homogeneous-sector economy.

of a susceptible household in the model is defined as

$$c_t^s = \left(\sum_{k=1,2} \upsilon_k^{1/\eta} (c_{tk}^s)^{1-1/\eta} \right)^{\eta/(\eta-1)} \tag{54}$$

whereas measured consumption of that same household is given by

$$c_t^j = \sum_{k=1,2} c_{tk}^j. \tag{55}$$

since prices of all goods are identical. Infected and recovered households optimally spread their consumption equally across sectors, and thus for these groups there is no difference between both consumption concepts.

By the goods market clearing condition, measured consumption (and thus measured GDP, since we abstract from investment and capital accumulation) equals aggregate labor input, which is therefore the relevant model variable for comparison to the empirically observed consumption decline.[9] As the lower right two panels show, measured consumption falls by slightly more than 8%, whereas the same statistic is more than 25% in the homogeneous sector ERT economy. Thus the reallocation mechanism reduces

[9]Evidently, as $\eta \to \infty$, the distinction between model consumption and measured consumption becomes irrelevant (as it is for the one-sector economy), but for smaller values this difference is quantitatively important.

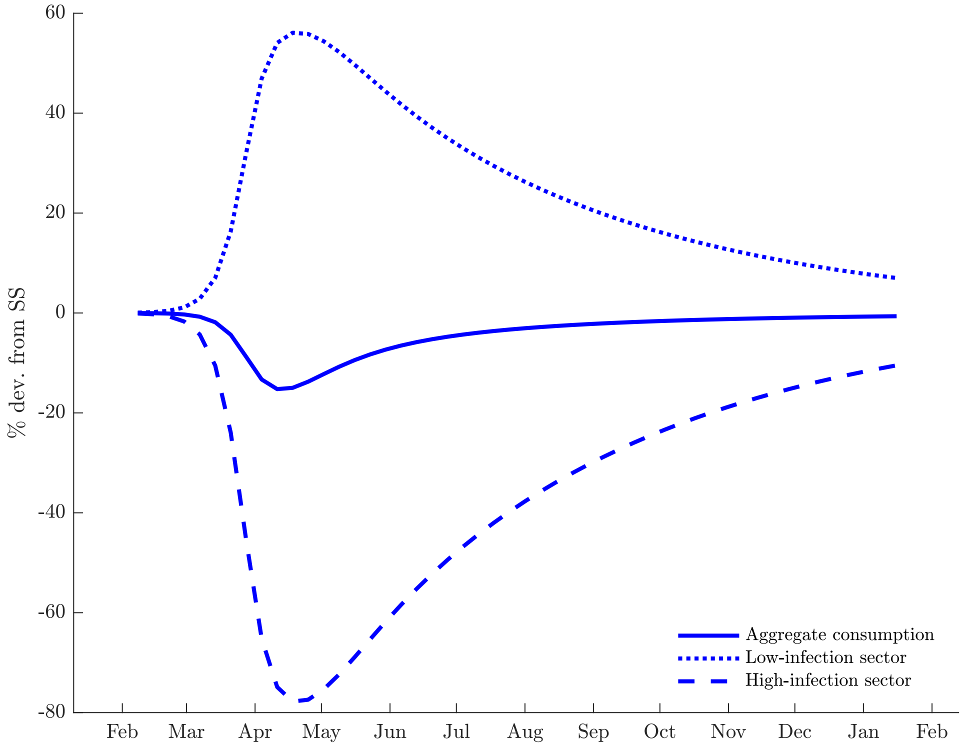


Figure 7: Sectoral dynamics.

the peak decline in economic activity by approximately 2/3.

As Fig. 6 also shows, sectoral reallocation significantly slows down the dynamic of the pandemic. As an unfortunately corollary, it also documents that the economy recovery takes long since it delays the time until the virus has run its course and herd immunity in society is attained. In the homogeneous sector economy this state would have been attained in the summer of 2020 already, albeit at the cost of close to 0.1% of the population having succumbed to the disease.

7 Sensitivity Analysis

7.1 Varying infection risks

Our choice of $\phi_1 = 0.2$ implies a much lower risk of infection in the low-infection sector, as compared to the high-infection sector. This in turn implies the massive reallocation across sectors displayed in Fig. 7 above, and strongly mitigates the decline in overall economic activity, as measured by the aggregate consumption and output decline in Fig. 6.

To assess the quantitative importance of the spread in infectiousness across sectors as measured by ϕ_1 we now document results for a lower dispersion of infectiousness across sectors, and choose $\phi_1 = 0.8$ We choose this value since, in addition to permitting us to vary significantly the importance of the

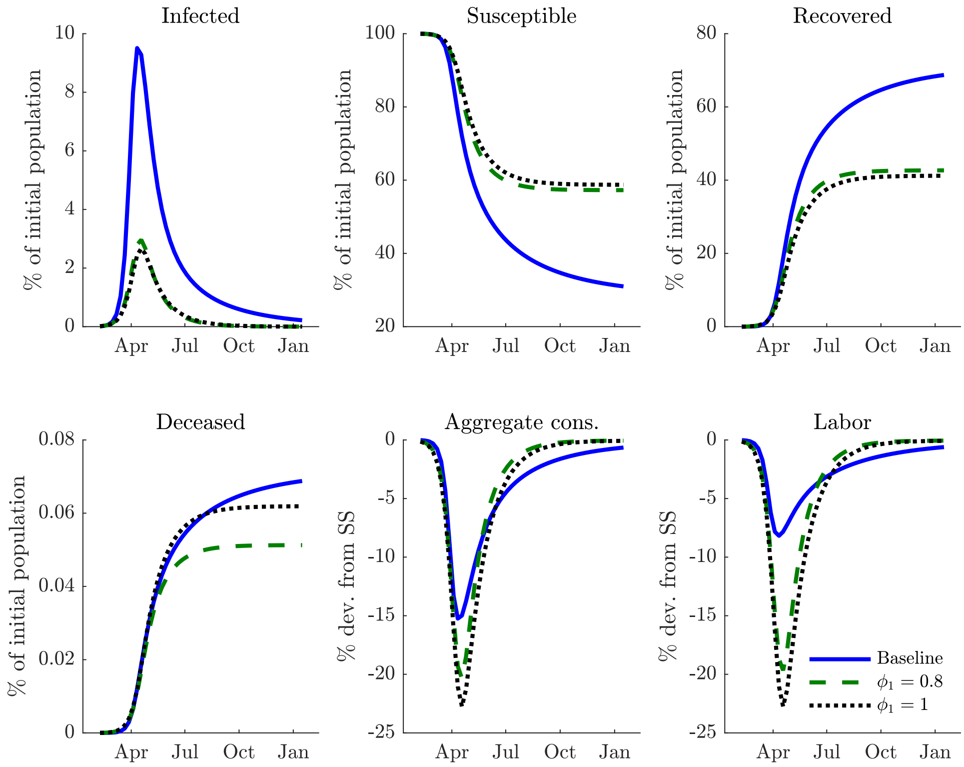


Figure 8: Dynamics with optimised parameters at various values of ϕ_1.

reallocation channel, it implies a shift in economic activities across sectors that accords well with Swedish disaggregated data on economic activity, as we will document below. A value $\phi_1 = 0.8$ implies a significantly smaller difference across consumption sectors in infection risks, and thus it leads to a weaker incentive to relocate consumption activity across sectors.

Table 2 demonstrates that once we re-estimate the model, under the new parameter values associated with $\phi_1 = 0.8$ the implied R_0 falls to 1.56, relative to a value of 3.24 in our baseline case when $\phi_1 = 0.2$. This is intuitive since now economic forces are weaker in mitigating the pandemic, and in order to fit the same death dynamics requires health parameters that imply a lower basic reproduction number, relative to a parameterization in which economic adjustments are strong.

In Fig. 8 we display the health- and economic dynamics in three economies that differ in $\phi_1 \in \{0.2, 0.8, 1\}$. It is important to note that for all three versions of the model the parameters have been re-estimated so as to provide the best fit to the weekly death data for Sweden.[10]

Compared to the benchmark economy with $\phi_1 = 0.2$, less potent reallocation triggers a much larger decline in aggregate consumption and production. In fact, the reduction of consumption and output amounts to approximately 20%, and is only moderately smaller than the corresponding fall in the rep-

[10]Therefore the health dynamics in the first four sub-panels of Fig. 8 differs for the representative sector economy ($\phi_1 = 1$), relative to Fig. 6 which did not re-estimate the parameters, in order to permit the clearest quantification of the reallocation mechanism.

resentative sector economy (compare the green dashed line with the black dotted line the the last two panels of Fig. 8. In addition, since both sectors now co-move much more, the distinction between the model CES-consumption aggregate and measured consumption is relatively unimportant, in contrast to the benchmark economy with $\phi_1 = 0.2$ where measured consumption declines much less (8%) than the CES consumption aggregate (15%). As a result of the much larger collapse of economic activity with $\phi_1 = 0.8$ relative to $\phi_1 = 0.2$, the infection curve has a lower peak now (see the first panel of Fig. 8.

In Fig. 9 we plot the evolution of sectoral consumption across two sectors, both in the model as well as in Swedish data. In the data, rather than restricting attention to narrowly defined sectors (such as restaurants and groceries, as in the introduction), we now use data on all final consumption sectors of the economy, rank them by their decline in the spring of 2020 relative to December 2019, and group them into two baskets according to this decline. We then plot the time series of output for both groups, relative to December 2019. The result is the right panel of Fig. 9. Appendix E contains the details of how the right panel of Fig. 9 is constructed

We observe that in the data, the consumption sectors that performed relatively well held almost steady, relative to the level of their activity at the end of 2019.[11]. In contrast, the sectors performing badly on average fell by 25% from December 2019 to May 2020, before recovering mildly. The aggregate consumption decline slightly exceeds 10% in April 2020. The data captures this pattern relatively well, although in the model for $\phi_1 = 0.8$ even the less infectious sector shows a non-negligible decline (4%) in April and May of 2020, relative to December 2019. The data also show a very mild reduction, but the decline never amount to more than 2% for that sector in the data. The gap between the two sectors is also somewhat larger in the model (at the peak decline, ca. 35% in the model v/s 25% in the data). Of course, as one drives ϕ_1 to one, the gap in the decline of consumption in both sectors coincide, and one obtains the homogeneous sector economy of ERT, and with it, the massive decline in aggregate consumption and production in excess of 20%.

7.2 Varying the Substitution Elasticity Across Goods

The second crucial parameter governing the quantitative importance of the sectoral substitution mechanism is the elasticity of substitution across sectors, as measured by η. As we have shown in the theoretical analysis, as the elasticity of substitution converges to zero, our model approximates the one-sector economy first studied by ERT. At the other extreme, as η approaches ∞, the substitution channel becomes maximally potent. Above, we showed that for our baseline parameterization of $\eta = 3$, measured consumption declines by about 8 percent, and the CES consumption aggregate by 15%. With a higher degree of substitution, $\eta = 10$, a value often used in New Keynesian models with differentiated goods,

[11] This aggregation masks nontrivial heterogeneity across more finely defined sectors, of course

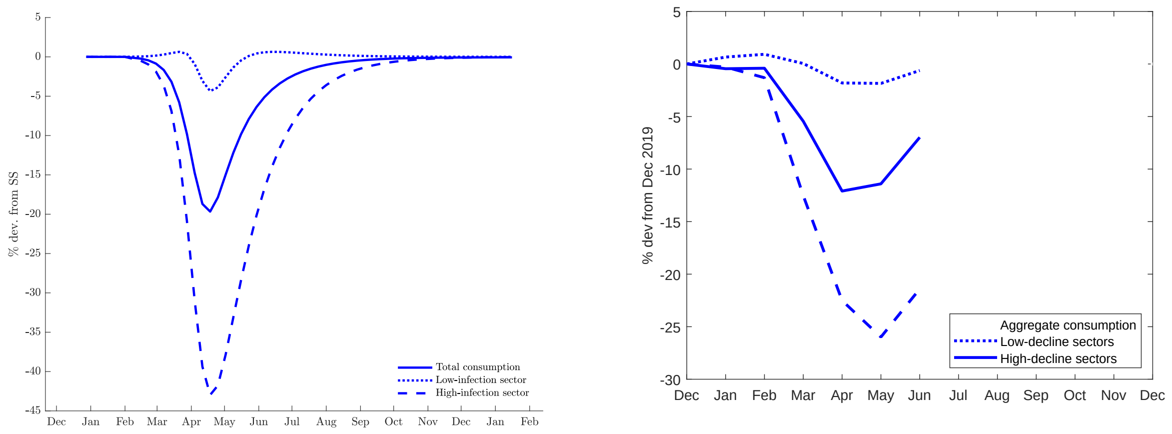


Figure 9: Sectoral dynamics when $\phi_1 = 0.8$ vs Swedish data.

the decline in consumption is is cut by about 60%, to 2.5% (measured consumption) and 6% (CES consumption aggregate). The infection curve is considerably flattened as well, compared to the benchmark case.

The comparison of $\eta = 3$ to $\eta = 10$ in Fig. 10 shows the importance of the substitution mechanism between goods: with a higher elasticity of substitution, households are more willing to substitute into the low-infection-risk sectors. Motivated by our theoretical results, Fig. 10 also contains cases where the elasticity of substitution is approaching infinity, i.e. $\eta = 100$ and $\eta = 1000$, the infection curve is not just flattened, it is reversed: the number of infected people decays on its own, and the disease is stopped in its tracks. This is consistent with Proposition 2. As Fig. 11 shows, for high values of η individuals shift close to 100% of their consumption activities to the less infectious sectors as the pandemic starts to take hold of the economy $\eta = 100$, or for the extreme case where $\eta = 1000$ this happens so early in the (would-be) pandemic (with sectoral reallocation complete as soon as a few Covid-19 cases emerge in the economy) that the disease hardly spreads to the susceptible population.

8 Socially Optimal Allocations

Lastly, we explore the solution to the social planner's problem described in section 4. Fig. 12 shows the outcome of the social planner solution (green line) in comparison to our baseline decentralized economy with $\eta = 3$ (blue line) as well as the homogeneous-sector case (black-dotted line).[12] The social planner essentially stops the outbreak dead in its tracks: the number of infected agents declines quickly, and is barely noticeable within a few weeks after the start of the outbreak. The social planner achieves

[12]The social planner solution for the homogeneous sector case (not plotted) is practically indistinguishable from the planner solution for the heterogeneous sector economy: as far as aggregates chosen by a *social planner* are concerned, sector heterogeneity plays practically no role.

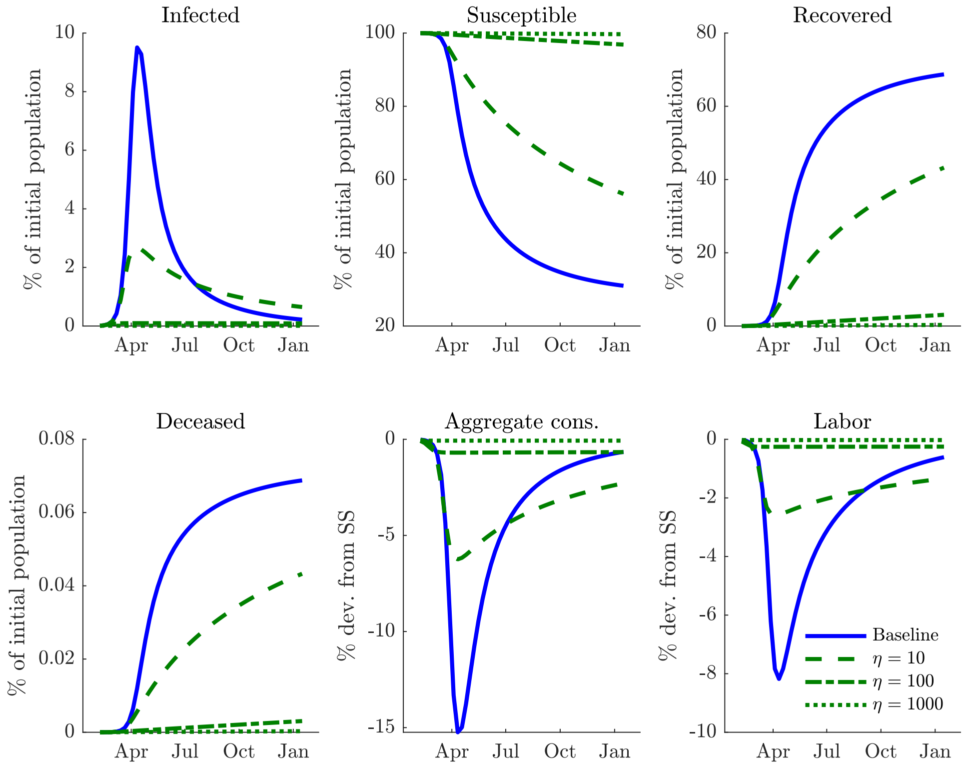


Figure 10: Heterogeneous-sector economy: variations in η.

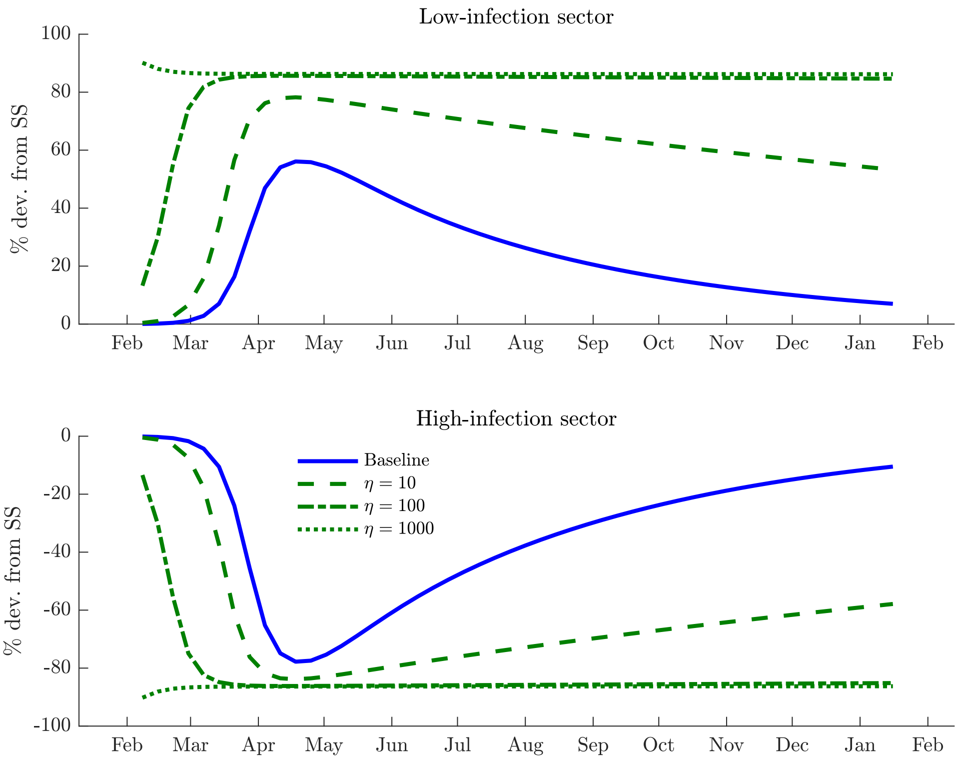


Figure 11: Heterogeneous-sector economy: consumption dynamics.

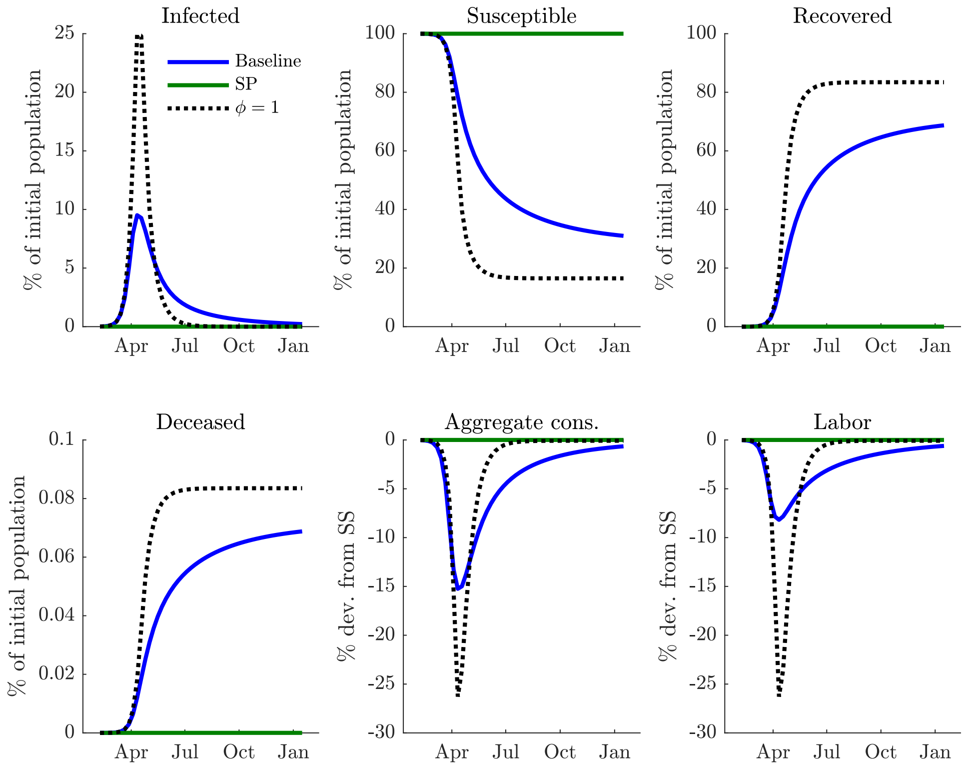


Figure 12: Heterogeneous-sector economy: social planning solution.

this outcome by restricting consumption of infected agents in a Draconian manner, thereby hugely mitigating the infection risk and stopping the infection at the onset. Compared to the competitive equilibrium outcome, a planner with the power to distinguish between the health status of infected and susceptible therefore is even more successful in averting the epidemic. However, as we saw above, private incentives together with substitution possibilities across sectors makes the epidemic much more benign already, relative to the one-sector economy studied in most of the literature. Thus, the wedge between equilibrium and socially optimal allocations is much smaller if private households are given more opportunity to shift activity away from highly infectious sectors. The additional powers afforded to the social planner are therefore less potent in our economy, relative to a world where private adjustments to the epidemic are more limited.

Fig. 13 further illustrates how the consumption of infected people is restricted, and how the allocation depends on the degree of substitutability between the two sectors. In the baseline scenario, the per capita consumption of an infected household is restricted to less than 17% of its steady state of the non-infectious competitive equilibrium. Consumption of infected individuals in the highly infectious sector is effectively driven to zero, especially if the two sectors are highly substitutable (the $\eta = 10$ case). Effectively, the planner insulates with large infection risk from infected individuals. In the benchmark case with lower elasticity of substitution, $\eta = 3$, the social planner does not impose quite as drastic a difference across the

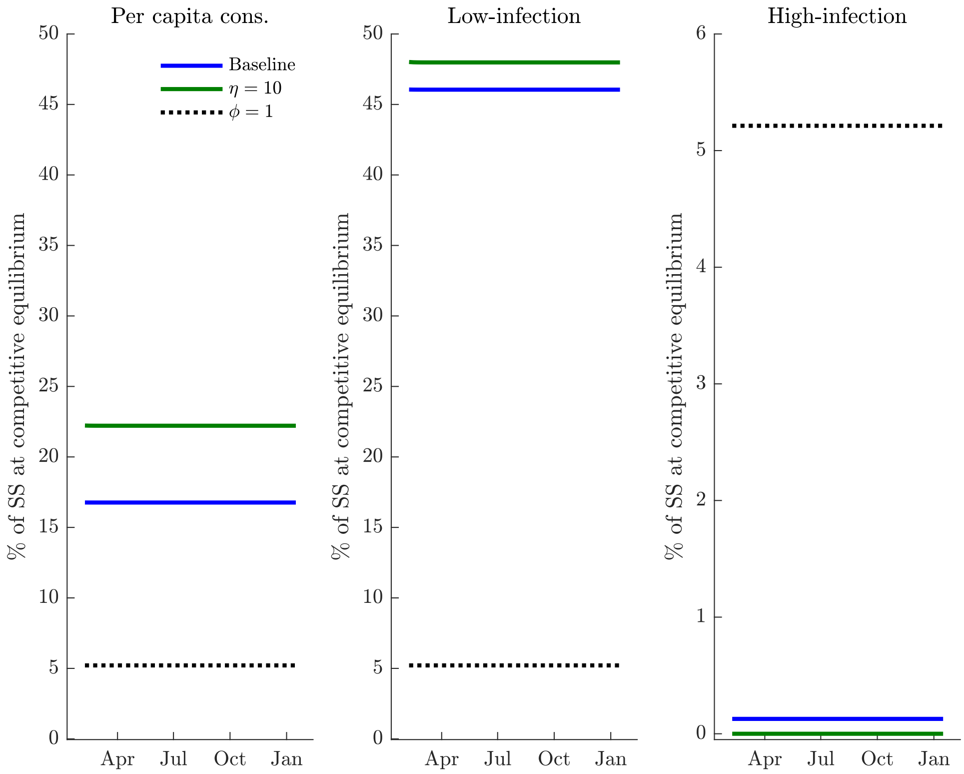


Figure 13: Per capita consumption of infected people.

sectors (since this would be very costly in terms of lifetime utility of the infected individuals, which the planner values as well). In the homogeneous sector case, alternatively, the case for $\eta = 0$, consumption in both sectors is the same, as the dotted-black line shows: now, consumption for the infected is reduced to only 5 percent of the non-infectious steady state. It is in this treatment of the infected, where the sectoral substitution possibilities matter considerably, since without the ability to insulate the infected from the susceptible population by other means, the planner finds it optimal to reduce consumption activity of the infected across the board in order to avoid the outbreak of the epidemic.

One should take the social planner solution with a grain of salt, of course. Presumably, a really powerful social planner would entirely separate the infected and recovered people from the susceptible people. If this is technologically feasible, the disease cannot spread any further, and no consumption decline for the infected is needed. The formulation of our social planner problem precludes this possibility. In summary, our calculations and this remark shows that the possibility for containing the pandemic depends crucially on the tools available to the government, and they may involve imposing considerable hardship on a few (the initially infected) in order to rescue the many.

9 Conclusion

In this paper, we have analyzed the laissez-faire approach or "Swedish" solution to the covid-19 pandemic. We built on the macroeconomic-cum-SIR model of Eichenbaum et al. (2020), but departed from their analysis in that we permit substitution of consumption across sectors with different degrees of infection probabilities. After presenting theoretical results for the limits of the elasticity of substitution between sectors, we quantified the model in particular by calibrating our epidemiological parameters to the Swedish death dynamics.

We found that our model fits that death dynamics substantially better than a plain-vanilla SIR model, while also providing a reasonably good fit to the overall consumption decline in Sweden. Our analysis implies case fatality rates below 0.2 percent and a limit of less than 800 death per million for Sweden. Here, one ought to keep in mind that the model does not allow for the possibility of a "second wave" or other time-varying features for the infection dynamics: thus, the shape of the weekly death dynamics data for Sweden exhibited in figure 2 allows the model no other conclusion, that Sweden is approaching herd immunity, i.e. is nearing the limit in the total death toll. Time will tell, whether this prediction will be borne out by future evidence.

We found that the decline in economic activity as well as the peak weekly death toll would have been three times as large compared to our benchmark calibration, when assuming the sectors to be homogeneous instead. Thus, the sectoral substitution possibility is a powerful force in mitigating the speed of the pandemic dynamics and the depth of the economic decline.

In the laissez-fare model, agents do not take the externality into account, that their infectious state and infection risk imposes on others. We therefore juxtaposed our laissez-fare solution to the solution of a social planner, who knows the health status of agents and can dictate their consumption and labor choices, but cannot otherwise separate individuals. The social planner would drastically lower the consumption of infected agents, thereby avoiding the economic decline and the pandemic dynamics practically entirely.

References

Adhmad, S. and D. Riker (2019, May). A method for estimating the elasticity of substitution and import sensitivity by industry. Economics WOrking Paper Series 2019-05-B, U.S. International Trade Commission.

Alvarez, F., D. Argente, and F. Lippi (2020, April). A simple planning problem for covid-19 lockdown. Draft, University of Chicago.

Atkeson, A. (2020, March). What will be the economic impact of covid-19 in the us? rough estimates of disease scenarios. NBER WP No. 26867.

Barrero, J., N. Bloom, and S. J. Davis (2020a). Covid-19 is also a reallocation shock. *draft, University of Chicago, Brookings Papers on Economic Activity, forthcoming*.

Barrero, J., N. Bloom, and S. J. Davis (2020b, September). Covid-19 is also a reallocation shock. *Research Briefs in Economic Policy, CATO Institute* (232).

Berger, D., K. Herkenhoff, and S. Mongey (2020). An seir infectious disease model with testing and conditional quarantine. BFI Working Paper NO. 2020-25.

Correia, S., S. Luck, and E. Verner (2020, March). Pandemics depress the economy, public health interventions do not: Evidence from the 1918 flu. Draft.

Dingel, J. and B. Neimann (2020). How many jobs can be done at home? *Covid Economics: Vetted and Real-Time Papers*.

Eichenbaum, M., S. Rebelo, and M. Trabandt (2020, March). The macroeonomics of epidemics. Draft, Northwestern University.

Fang, H., L. Wang, and Y. Yang (2020, March). Human mobility restrictions and the spread of the novel coronavirus (2019-ncov) in china. Working Paper 26906, National Bureau of Economic Research.

Farboodi, M., G. Jarosch, and R. Shimer (2020). Internal and external effects of social distancing in a pandemic. Working Paper, University of Chicago.

Fernandez-Villaverde, J. (2010). The econometrics of DSGE models. *SERIEs 1*, 3–49.

Glover, A., J. Heathcote, D. Krüger, and J.-V. Rios-Rull (2020, April). Health versus wealth: On the distributional effects of controlling a pandemic. Draft.

Gómez, V. and A. Maravall (1997). Programs tramo and seats: instructions for the user. Mimeo, Banco de España.

Greenstone, M. and V. Nigam (2020). Does social distancing matter? (March 30, 2020). University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2020-26. Available at SSRN: https://ssrn.com/abstract=3561244 or http://dx.doi.org/10.2139/ssrn.3561244.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020, March). Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? Draft, MIT.

Kaplan, G., B. Moll, and G. Violante (2020, March). Pandemics according to HANK. Draft, University of Chicago.

Leibovici, F., A. M. Santacreu, and M. Famiglietti (2020). Social distancing and contact-intensive occupations. *On the economy, St. Louis FED*.

Mongey, S. and A. Weinberg (2020, March). Characteristics of workers in low work-from-home and high personal-proximity occupations. Draft, University of Chicago.

Sax, C. and D. Eddelbuettel (2018). Seasonal adjustment by x-13arima-seats. *R. Journal of Statistical Software*.

Toxvaerd, F. (2020). Equilibrium social distancing. Cambridge-INET Working Paper 2020/08.

A Two-sector simulations

The consumer interaction indicator $\phi(k)$ is defined piece-wisely as

$$\phi(k) = \begin{cases} \phi_1 & k \in [0, \upsilon) \\ \phi_2 & k \in [\upsilon, 1] \end{cases}$$

where υ is the size of the sector with lower consumer interactions. For each sector $j \in \{1, 2\}$, there is a first-order condition with respect to c^x_{jt}, where $x \in \{s, i, r\}$. The equations for infected and recovered people are substituted out, because their consumption and labor are constant. The following equations consist the system delivering the paths of key variables.

$$\upsilon_1^{1/\eta} \tfrac{1}{c_t^s} \left(\tfrac{c_t^s}{c_{1t}^s}\right)^{1/\eta} = \frac{\theta}{A} n_t^s + \pi_s I_t \lambda_{\tau,t} \phi_1 \frac{A}{\sqrt{\theta}} \tag{A.1}$$

$$\upsilon_2^{1/\eta} \tfrac{1}{c_t^s} \left(\tfrac{c_t^s}{c_{2t}^s}\right)^{1/\eta} = \frac{\theta}{A} n_t^s + \pi_s I_t \lambda_{\tau,t} \phi_2 \frac{A}{\sqrt{\theta}} \tag{A.2}$$

$$c_{1t}^s + c_{2t}^s = A n_t^s \tag{A.3}$$

$$c_t^s = \left[\upsilon_1^{1/\eta} {c_{1t}^s}^{1-1/\eta} + \upsilon_2^{1/\eta} {c_{2t}^s}^{1-1/\eta}\right]^{\frac{\eta}{\eta-1}} \tag{A.4}$$

$$\lambda_{\tau,t} = -\beta \left(U_{t+1}^i - U_{t+1}^s\right) \tag{A.5}$$

$$U_t^s = u\left(c_t^s, n_t^s\right) + \beta \left[\left(1 - \tau_t\right) U_{t+1}^s + \tau_t U_{t+1}^i\right] \tag{A.6}$$

$$U_t^i = u\left(c^i, n^i\right) + \beta \left[\left(1 - \pi_d\right) U_{t+1}^i + \pi_r U_{t+1}^r\right] \tag{A.7}$$

$$U_t^r = u\left(c^i, n^i\right) + \beta U_{t+1}^r \tag{A.8}$$

$$\tau_t = \frac{A}{\sqrt{\theta}} \pi_s I_t \left(\phi_1 c_{1t}^s + \phi_2 c_{2t}^s\right) \tag{A.9}$$

$$T_t = \tau_t S_t \tag{A.10}$$

$$S_t = 1 - I_t - R_t - D_t \tag{A.11}$$

$$R_t = R_{t-1} + \pi_r I_{t-1} \tag{A.12}$$

$$D_t = D_{t-1} + \pi_d I_{t-1} \tag{A.13}$$

$$I_t = T_{t-1} + \left(1 - \pi_d - \pi_r\right) I_{t-1} + 1_{t=1} \varepsilon \tag{A.14}$$

Note that the time convention of disease dynamics is modified for implementation in Dynare. An MIT shock of size ε is added to (A.14) in period 1. The paths of aggregate consumption and labor are given by

$$C_t = S_t c_t^s + (I_t + R_t)\frac{A}{\sqrt{\theta}} \tag{A.15}$$

$$N_t = S_t n_t^s + (I_t + R_t)\frac{1}{\sqrt{\theta}} \tag{A.16}$$

B Eliminating c_{tk}^s

Note that $c_{tk}^i = A/\sqrt{\theta}$. Let us reexamine (13) and write it as

$$\left(\frac{c_t^s}{c_{tk}^s}\right)^{1/\eta} = x_{tk} \tag{B.1}$$

where we define

$$x_{tk} = c_t^s\left(\lambda_{bt}^s + \nu_t\phi(k)A/\sqrt{\theta}\right) \tag{B.2}$$

Rewrite (B.1) as

$$c_{tk}^s = x_{tk}^{-\eta}c_t^s \tag{B.3}$$

Thus

$$(c_{tk}^s)^{1-1/\eta} = x_{tk}^{1-\eta}(c_t^s)^{1-1/\eta} \tag{B.4}$$

and integrate

$$\int (c_{tk}^s)^{1-1/\eta}dk = \int x_{tk}^{1-\eta}dk \times (c_t^s)^{1-1/\eta}$$

Taking this to the power $\eta/(\eta-1)$ finally yields

$$c_t^s = \left(\int x_{tk}^{1-\eta}dk\right)^{\eta/(\eta-1)} c_t^s$$

or the constraint

$$1 = \left(\int x_{tk}^{1-\eta}dk\right)^{\eta/(\eta-1)}$$

This can be simplified to

$$1 = \int x_{tk}^{1-\eta} dk \tag{B.5}$$

or

$$c_t^s = \left(\int \left(\lambda_{bt}^s + \nu_t \phi(k) A/\sqrt{\theta} \right)^{1-\eta} dk \right)^{1/(1-\eta)} \tag{B.6}$$

Thus, (4) and (5) can be rewritten as

$$\begin{aligned} \tau_t &= \pi_s I_t \int \phi(k) x_{tk}^{\eta} c_t^s A/\sqrt{\theta} dk & \text{(B.7)} \\ &= \pi_s I_t \int \phi(k) \left(\lambda_{bt}^s + \nu_t \phi(k) A/\sqrt{\theta} \right)^{-\eta} (c_t^s)^{1-\eta} A/\sqrt{\theta} dk & \text{(B.8)} \end{aligned}$$

and

$$\begin{aligned} T_t &= \pi_s S_t I_t \int \phi(k) x_{tk}^{\eta} c_t^s A/\sqrt{\theta} dk & \text{(B.9)} \\ &= \pi_s S_t I_t \int \phi(k) \left(\lambda_{bt}^s + \nu_t \phi(k) A/\sqrt{\theta} \right)^{-\eta} (c_t^s)^{1-\eta} A/\sqrt{\theta} dk & \text{(B.10)} \end{aligned}$$

C Details for the Heterogeneous Labor Economy

Proof of Proposition 4. To see the similarities and differences between the heterogeneous consumption- and heterogeneous labor economy more formally, observe that the first order conditions for infected and recovered agents are unchanged. In particular, we obtain $c_t^i = c_{tk}^i \equiv A/\sqrt{\theta}$ and $n_t^i = n_{tk}^i = 1/\sqrt{\theta}$, regardless as to whether consumption or labor is heterogeneous and regardless of the particular approach taken for labor heterogeneity. It therefore suffices to examine the first order conditions for susceptible agents.

For the consumption-infection baseline model, the first-order conditions can be summarized by

$$\frac{1}{c_t^s} \left(\frac{c_t^s}{c_{tk}^s} \right)^{1/\eta} - \frac{\theta}{A} n_t^s = \pi_s \phi_k \lambda_{\tau t} \frac{A}{\sqrt{\theta}} I_t \tag{C.1}$$

while the aggregation constraint and budget constraint are

$$\begin{aligned} c_t^s &= \left(\int (c_{tk}^s)^{1-1/\eta} dk \right)^{\eta/(\eta-1)} \\ A n_t^s &= \int c_{tk}^s dk \end{aligned}$$

Define $n^s_{tk} = c^s_{tk}/A$ and rewrite these two equations equivalently as

$$c^s_t = A\left(\int (n^s_{tk})^{1-1/\eta}\, dk\right)^{\eta/(\eta-1)} \tag{C.2}$$

$$n^s_t = \int n^s_{tk} dk \tag{C.3}$$

Recall that the infection probability is given by equation (4). Substituting out the solution for c^i_t as well as c^s_{tk} with $An^s_{tk} = c^s_{tk}$, it can be restated as

$$\tau_t = \pi_s I_t \int \phi(k) A n^s_{tk} dk \frac{A}{\sqrt{\theta}} + \pi_a I_t, \tag{C.4}$$

For the production-based heterogeneous-labor model, the first-order conditions can be summarized by

$$\frac{1}{c^s_t}\left(\frac{n^s_t}{n^s_{tk}}\right)^{1/\alpha} - \frac{\theta}{A} n^s_t = \frac{\tilde{\pi}_s}{A}\phi_k \lambda_{\tau t}\frac{1}{\sqrt{\theta}} I_t \tag{C.5}$$

while the aggregation constraint and budget constraint are

$$c^s_t = A\left(\int (n^s_{tk})^{1-1/\alpha}\, dk\right)^{\alpha/(\alpha-1)} \tag{C.6}$$

$$n^s_t = \int n^s_{tk} dk \tag{C.7}$$

Recall that the infection probability is given by equation (45), which can be restated as

$$\tau_t = \tilde{\pi}_s I_t \int \phi(k) n^s_{tk} dk \frac{1}{\sqrt{\theta}} + \pi_a I_t, \tag{C.8}$$

For $\alpha = \eta$, $\tilde{\pi}_s = A^2 \pi_s$ and $n^s_{tk}/n^s_t = c^s_{tk}/c_t$, equations (C.5) becomes (C.1), equations (C.6) become equations (C.2) and (C.8) becomes (C.4). □

For the preference-based heterogeneous-labor formulation, the first-order conditions can be summarized by

$$\frac{1}{c^s_t} - \frac{\theta}{A} n^s_t \frac{f'(n^s_{tk})}{f'(n^s_t)}\left(\frac{f(n^s_t)}{f(n^s_{tk})}\right)^{1/\alpha} = \frac{\tilde{\pi}_s}{A}\phi_k \lambda_{\tau t}\frac{1}{\sqrt{\theta}} I_t \tag{C.9}$$

while the aggregation constraint and budget constraint are

$$c^s_t = A\int n^s_{tk} dk \tag{C.10}$$

$$n^s_t = \left(\int (n^s_{tk})^{1-1/\alpha}\, dk\right)^{\alpha/(\alpha-1)} \tag{C.11}$$

While there is considerable formal similarity, there no longer is a formal equivalence as in proposition 4.

D First Order Conditions of the Social Planner Problem

The social planner's problem in the main text yields the following first-order conditions:

$$
\begin{aligned}
&\left(\frac{\partial}{\partial c_t^s}:\right) && u_{1,t}^s\left(\frac{c_t^s}{c_{tk}^s}\right)^{1/\eta}+\mu_{f,t} && =\beta\pi_s\phi\mu_{I,t+1}I_tc_{tk}^i\\
&\left(\frac{\partial}{\partial c_t^i}:\right) && u_{1,t}^i\left(\frac{c_t^i}{c_{tk}^i}\right)^{1/\eta}+\mu_{f,t} && =\beta\pi_s\phi\mu_{I,t+1}S_tc_{tk}^s\\
&\left(\frac{\partial}{\partial c_t^r}:\right) && u_{1,t}^r\left(\frac{c_t^r}{c_{tk}^r}\right)^{1/\eta}+\mu_{f,t} && =0\\
&\left(\frac{\partial}{\partial n_t^s}:\right) && u_{2,t}^s && =\mu_{f,t}A\\
&\left(\frac{\partial}{\partial n_t^i}:\right) && u_{2,t}^i && =\mu_{f,t}A\\
&\left(\frac{\partial}{\partial n_t^r}:\right) && u_{2,t}^r && =\mu_{f,t}A\\
&\left(\frac{\partial}{\partial S_t}:\right) && u\left(c_t^s,n_t^s\right)+\mu_{f,t}\int c_{tk}^s dk+\mu_{S,t} && =\mu_{f,t}An_t^s\\
& && && +\beta\left[\mu_{S,t+1}+\mu_{I,t+1}\pi_sI_t\int\phi(k)c_{tk}^sc_{tk}^i dk\right]\\
&\left(\frac{\partial}{\partial I_t}:\right) && u\left(c_t^i,n_t^i\right)+\mu_{f,t}\int c_{tk}^i dk+\mu_{I,t} && =\mu_{f,t}An_t^i-\mu_{S,t}\\
& && && +\beta\left[\left(\mu_{S,t+1}+\mu_{I,t+1}\right)\left(1-\pi_r-\pi_d\right)\right.\\
& && && \left.+\pi_r\mu_{R,t+1}+\mu_{I,t+1}\pi_sS_t\int\phi(k)c_{tk}^sc_{tk}^i dk\right]\\
&\left(\frac{\partial}{\partial R_t}:\right) && u\left(c_t^r,n_t^r\right)+\mu_{f,t}\int c_{tk}^r dk+\mu_{R,t} && =\mu_{f,t}An_t^r+\beta\mu_{R,t+1}
\end{aligned}
$$

E Replicating data

Replicating Figure 1

Navigate to the *Statistical Database* module of the *Statistics Sweden* website and use their GUI to extract all *Fixed Price* denominated rows from the **Monthly Indicator for Household Consumption**[13]. This index details trends in retail trade, wholesale trade, and other service industries, and spans 20 years from January 2000 to July 2020. Transpose and subset this dataframe until only 3 columns remain: *Total Consumption*, *Restaurants*, and *Groceries.*

Control for seasonality (e.g. Christmas spending spikes) in these 3 columns by following along with

[13] www.statistikdatabasen.scb.se/pxweb/en/ssd/START__HA__HA0101__HA0101B/HushKonInd/

Sax and Eddelbuettel (2018) in their aptly named paper, *Seasonal Adjustment by X-13ARIMA-SEATS in R*, which presents a model selection framework for linear regression models with ARIMA errors. This paper builds upon a SEATS procedure originally developed by Gómez and Maravall (1997) at the Bank of Spain.

Once deseasonalized, rebase each of the 3 columns so that December 2019 is always equal to 100, by dividing all the points in each series by the value of said series at 2019M12 and multiplying by 100. The resulting deseasonalized and rebased dataset gives us a clearer picture of what is happening. Plotting the last 12 rows of these 3 columns should now flawlessly replicate Figure 1.

Replicating figure 9

Extract two new dataframes from the *Statistics Sweden* repository: **GDP (Production Approach) by Industrial Classfication**[14] and **Turnover Index for the Service Sector**[15], denoted respectively in *Constant Prices (SEK Millions)* and *Volume (Fixed Prices)*. While GDP (Production Approach) measures GDP as the sum of the values added by all sectors of the economy, the Turnover Index is a survey tracking monthly changes in invoice sales. Turnover Index is used an input for national accounts statistics. Go ahead and deseasonalize/rebase each column in Turnover Index just as in Figure 1.

A "mean response to Covid" for each industry is then constructed, defined as the mean value of the index for each sector during the first 6 months of 2020. This metric is used to ordinally rank each sector in the Turnover Index, from those most impacted by Covid (e.g. airlines/hotels) to those least impacted (e.g. veterinarians, IT services).

Next, filter the GDP (Production Approach) dataframe so that it contains only values for 2019Q1, 2019Q2, 2019Q3, and 2019Q4, then sum these 4 quarters to obtain total GDP for 2019. This nominal amount for each sector is then divided through by the entire sum for all sectors, so that the weights sum to one. We have now ascertained the relative size of each sector.

We now wish to link/merge these two dataframes (GDP & Turnover); at first glance this might seem straightforward as they both rely on NACE (Nomenclature des Activités Économiques dans la Communauté Européenne) classification codes. However, upon closer inspection, one realizes that the variables in the two datasets do not match up perfectly; some miscellaneous data cleaning practices and subjective choices are required to build our own bespoke consumption bundle, a bundle seeking to proxy for *Total Consumption* in Figure 1. Many columns are dropped outright because they are contained in one dataframe but not the other; other columns are dropped because they are superfluous or do not proxy for consumption. Other columns must be aggregated, for example sectors 94, 95, and 96 in the Turnover Index are averaged into one new variable dubbed 94-96, because while GDP (Production Approach) does

[14] www.statistikdatabasen.scb.se/pxweb/en/ssd/START__NR__NR0103__NR0103A/NR0103ENS2010T06Kv/
[15] www.statistikdatabasen.scb.se/pxweb/en/ssd/START__HA__HA0101__HA0101B/DivtjansterM07X/

not contain any of 94, 95, or 96, it does contain a variable called 94-96. This aggregation is a workaround that lets us compare the two dataframes. The entire cleaning and linking process is described in detail in our accompanying R code, and whittles our initial dataframes down from 60+ miscellaneous sectors down to a core 14 sectors. Depending on the choices you (the replicator) make, your particular dataset may have roughly more or less than 14 sectors, depending on how you aggregate/drop columns, and how you choose to define Total Consumption.

Finally, classify all sectors in this newly linked dataframe into those that boomed the most vs. those that declined the most due to Covid. This is done simply by sorting the dataframe on “mean response to Covid”, as calculated two paragraphs ago. Add together all the sectors with the highest mean response until their cumulative sum of GDP contributions gets just over 0.5, and plot the time series. Congratulations, you have now successfully replicated Figure 2! Should you wish to replicate Figure 3 (5-sectors) instead, simply set cutoffs at the 0.2, 0.4, 0.6, & 0.8 thresholds, instead of one single cutoff at 0.5.