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Pandemic Containment and Inequality in a Developing Economy*

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Abstract

We integrate a canonical SIR epidemiological model into a general equilibrium framework with high-skill and low-skill workers, each choosing to work either from their work locations (onsite) or from their homes (remote). Onsite and remote labour are imperfect substitutes, but more substitutable for high-skill relative to low-skill workers. Calibrating the model to the Indian economy, we find that different containment policies, by restricting onsite labour, disproportionately affects low-skill compared to high-skill workers, thereby worsening the already existing inequality. Furthermore, the containment policies are less effective in controlling disease spread among low-skill workers as they optimally choose to work more onsite in comparison to their high-skill counterparts. Finally, we show that conditional transfers for low-skill workers designed to neutralize the increased inequality generated by lockdown, increases the effectiveness of various containment policies and succeeds in reducing the disparity in health outcomes between high-skill and low-skill workers.

Keywords: COVID-19, Containment, Inequality, Transfers

1. Introduction

In December 2019, a virus started to spread among the population in the Chinese city of Wuhan. In less than four months, the viral disease turned into a pandemic, killing thousands, infecting hundreds of thousands, overwhelming health care systems and literally bringing entire countries to a standstill. Covid-19, or the coronavirus disease (2019) has, as of now, infected more than 4.5 million people in 210 countries, while killing more than 300,000.

To contain the spread of the disease, governments around the world have put in place various containment measures, that varies from the relatively benign, such as carrying out day-to-day activities while maintaining social distancing, to the extreme, such as complete shutdowns where people are prevented from stepping out of their homes. But as entire sectors of the economy have stopped functioning due to these containment measures, the effect on average income has been devastating. Moreover, the uncertainty surrounding the disease has made it difficult to predict the full economic and health impact once the pandemic subsides.

In this paper, we attempt to do just that. We embed a canonical epidemiological model of a pandemic into a dynamic, general equilibrium model of production and consumption in order to quantify the effect of Covid-19 on both economic as well as health outcomes. In the model, production is carried out by two types of workers: high-skill and low-skill. At the forefront of our analysis is the observation that workers have the option of working either from their work-sites or from their homes. The labour supplied from their work-sites (onsite labour) and the labour supplied from their homes (remote labour) are imperfect substitutes. Moreover, the nature of work in high-skill occupations makes onsite labour for high-skill workers far more substitutable compared to low-skill workers.

Next, we examine the quantitative implications of the model. Calibrating the model to India and experimenting with different containment policies, we find that there is a clear trade-off between containment of infections on the one hand and its effect on economic activity on the other. The policies that are most effective in reducing disease transmission also inflicts the greatest economic loss. More importantly, we find that every containment policy affects low-skill workers more adversely compared to high-skill workers on *both economic and health front*.

The intuition for the above result is as follows: because every policy imposes restriction on labour mobility and onsite labour is much less substitutable for low-skill workers, these policies disproportionately impact the labour income of low-skill workers compared to their high-skill counterparts. This worsens the already existing consumption inequality between these two kinds of workers. For example, across the different containment scenarios, inequality rises by between 3 percent and 21 percent over a period of roughly one year. On top of that, because low-skill workers cannot afford to completely substitute towards remote labour, they choose to work more onsite compared to the high-skill workers. This causes the containment policies to be less effective in reducing the spread of infections among low-skill workers.

How much transfer will be required to reduce the lockdown-induced consumption inequality to its pre-pandemic level? Depending on the containment policy under consideration, the cost of such a transfer to the low-skill workers could range from 0.06 to 0.29 percent of GDP. We find that these transfers, apart from the reversing the increase in inequality, also improve the effectiveness of the lockdown policies in containing the pandemic. By reducing the incentive of low-skill workers to venture out for work, these transfers control the infections and disease spread in the economy. Even though the cutback of low-skill labour has a negative effect on output, the decreased infection risk causes the high-skill workers to supply more onsite labour compared to the no-transfer case, thus having a positive effect on output.

There has been a number of recent papers analysing the impact of the pandemic and containment measures on different economic and health outcomes. Atkeson (2020) introduces the SIR model to economists and talks about the economic impact of COVID-19 in the US. Eichenbaum et al. (2020) extends a canonical epidemiology model with a general equilibrium framework to model the interaction between economic decisions and the spread of infections. Farboodi et al. (2020) integrates individual optimization decisions into an epidemiological model to study the social distancing outcomes in the US. Glover et al. (2020) talks about the distributional effects of containment policies in the US where the individuals differ by age, sectors and health status. Kaplan et al. (2020) also talks about substitutability of onsite and remote labour in a HANK model and talks about the implications for US. And, there are a number of recent empirical contributions that talk about the heterogeneous impacts of social distancing policies on different occupations (Montenovo et al. (2020); Mongey et al. (2020); Dingel and Neiman (2020)). Using O*NET data for the US, they argue that the workers belonging to occupations having low ability to work from home are worse affected by this pandemic, in line with our findings. Our paper attempts to study the impact of containment policies on economic and health inequality in a developing economy, India, which is characterized by a large fraction of low-skill workers whose ability to supply remote labour is severely limited.

The rest of the paper is organized as follows. Section 2 describes the model and derives the equilibrium conditions. Section 3 presents the calibration strategy while the main results of the paper are discussed in section 4. Section 5 concludes.

2. The Model

This section presents the economy before the start of the pandemic and follows it up with the economy during the pandemic. In particular, we extend the model proposed by Eichenbaum et al. (2020) to two types of workers (high-skill and low-skill) supplying two types of labour (onsite and remote). In our framework, the containment policy is modeled as a negative productivity shock to the onsite labour.

2.1 Pre-Pandemic Economy

The economy consists of a unit measure of workers out of which ψ fraction is high-skill while $1-\psi$ of them is low-skill. The workers, apart from choosing consumption, can supply two different kinds of labour. The labour that is supplied at the work location is called *onsite* labour (n) while working from home is called *remote* labour $(\hat{n})$. Onsite and remote labour are imperfect substitutes, but more substitutable for high-skill workers compared to low-skill workers.

Before the pandemic, the high-skill (and similarly low-skill) workers maximize their lifetime utility

$$U^j = u(c^j, n^j, \hat{n}^j) + \beta U^j,$$

where c^j refers to consumption of worker $j \in \{h, l\}$, while n^j and $\hat{n}^j$ refers to the onsite and remote labour respectively. The budget constraint of a worker is given by

$$c^j = w^j \Big((1-\mu) n^j + \eta^j \hat{n}^j \Big) + \Gamma^j,$$

where w^j denotes the wage of worker j, η^j represents the elasticity of substitution between onsite (n^j) and remote $(\hat{n}^j)$ labour[1], and the total labour supplied by worker j is given by $((1-\mu)n^j + \eta^j \hat{n}^j)$. In the event of a lockdown imposed during a pandemic, remote labour becomes an integral part of labour supply as opposed to onsite labour in normal times. In this situation, the degree of substitutability between onsite and remote work becomes critical to determine the effective labour supply. In particular, lower is η_j, less effective is remote labour relative to onsite labour.

As high-skill workers belong to occupations that can be more readily performed from their homes compared to low-skill workers, any lockdown imposed to curtail the pandemic will disproportionately affect the economic well-being of low-skill workers compared to high-skill workers. We calibrate the elasticities η^h and η^l to find that η^l is far smaller compared to η^h in line with our prior expectations. The section on calibration provides more details on this.

We model the different containment measures as a negative productivity shock affecting onsite labour. μ refers to the containment rate and $(1-\mu)$ is the resulting productivity of onsite labour. This negative productivity shock makes onsite labour more expensive, hence discouraging people from heading out of their homes and incentivizing remote labour. Finally, Γ^j denotes the transfers the workers receive from the government. Initially, we set $\Gamma^j = 0$ but later solve for optimal transfers that minimizes the inequality generated because of various containment policies.

Assuming a utility function of $u(c^j, n^j, \hat{n}^j) = log(c^j) - \frac{\theta}{2}(n^j)^2 - \frac{\hat{\theta}}{2}(\hat{n}^j)^2$, the first-order

[1]The term elasticity of substitution is not fully accurate because η_j is meant to capture the difficulty of substituting onsite labour with remote labour and not the other way round.

conditions for worker j are:

$$\begin{aligned} n^j &= \frac{w^j(1-\mu)}{\theta c^j}, \\ \hat{n}^j &= \frac{w^j \eta^j}{\hat{\theta} c^j}. \end{aligned}$$

As can be seen from the above labour supply functions, containment rate μ acts as a deterrent for supplying onsite labour while η^j captures the cost of remote labour due to imperfect substitutability.

There is a continuum of competitive firms who hire both high-skill (L^h) and low-skill (L^l) workers to produce the consumption good (Y). The firm maximizes its profit

$$\Pi = AL - w^h N^h - w^l N^l,$$

where the firm combines high-skill and low-skill labour using a CES aggregator:

$$L = [\gamma^{1/\delta}(L^h)^{\frac{\delta-1}{\delta}} + (1-\gamma)^{1/\delta}(L^l)^{\frac{\delta-1}{\delta}}]^{\frac{\delta}{\delta-1}}.$$

Here γ captures the differences in productivity of high-skill and low-skill labour while δ denotes the elasticity of substitution between them.

In equilibrium, total output must equal total consumption:

$$Y = AL = \psi c^h + (1-\psi)c^l.$$

And finally, labour markets for both types of workers must clear:

$$\begin{aligned} L^h &= \psi((1-\mu)n^h + \eta^h \hat{n}^h), \\ L^l &= (1-\psi)((1-\mu)n^l + \eta^l \hat{n}^l). \end{aligned}$$

2.2 During Pandemic

Having developed the general equilibrium framework, we integrate it with the widely used SIR (Susceptible, Infected, Recovered) model proposed by Kermack and McKendrick (1927). With the advent of a pandemic, the population can be divided into four subgroups, namely susceptible (those who have not been infected), infected (those who have the disease), recovered (those who have been treated of the disease) and deceased (those who did not survive the infection). Both high-skill and low-skill workers can be separated into these four groups. Let the number of high-skill workers in these groups be S_t^h, I_t^h, R_t^h and D_t^h while the corresponding numbers for low-skill workers be S_t^l, I_t^l, R_t^l and D_t^l. Let T_t^h and T_t^l be the number of newly infected people at time t respectively.

The susceptible population can get infected in three different ways. First channel is through consumption. Susceptible people can meet infected people while purchasing consumption goods, and this in turn, can lead to new infections. The number of newly infected high-skill workers is given by $\pi_{s1}(S_t^h C_t^{S,h})(I_t C_t^I)$ while that of low-skill workers is given by $\pi_{s1}(S_t^l C_t^{S,l})(I_t C_t^I)$. Terms $(S_t^h C_t^{S,h})$ and $(S_t^l C_t^{S,l})$ represent the total consumption of high-skill and low-skill workers who are susceptible, while $(I_t C_t^I)$ represents the total consumption of all the infected people.[2] π_{s1} denotes the probability of infection through the consumption channel. As a susceptible person coming across an infected person, there is a chance of getting infected irrespective of whether the infected individual is high-skill or low-skill. Hence, the disease spread in both high and low-skill sectors depends on the total consumption of the infected population $(I_t C_t)$. But because the consumption patterns are different for high-skill and low-skill workers, the disease incidence might be different.

The second channel of transmission is through the interactions at place of work. The number of newly infected high-skill workers through this channel is $\pi_{s2}(S_t^h N_t^{S,h})(I_t N_t^I)$ and that of low-skill is $\pi_{s2}(S_t^l N_t^{S,l})(I_t N_t^I)$. The disease transmission does not depend on the entire labour supply, but only on the time spent at the place of work. $(S_t^h N_t^{S,h})$ and $(S_t^l N_t^{S,l})$ represents the total hours of onsite labour supplied by susceptible high-skill

[2] Total consumption of all infected population is given by $(I_t C_t^I) = I_t^h C_t^{I,h} + I_t^l C_t^{I,l}$

and low-skill workers respectively. As before, the transmission for high-skill and low-skill workers depend on the total amount of onsite labour $(I_t N_t^I)$ supplied by all the infected workers.[3] Because the low-skill workers belong to occupations that have a lower flexibility for remote labour, they could be more vulnerable in the face of a pandemic.

The third channel is the transmission through random meetings of susceptible and infected people other than consumption and labour channels. The number of newly infected high-skill and low-skill workers through this channel are $\pi_{s3} S_t^h I_t$ and $\pi_{s3} S_t^l I_t$ respectively. The total number of newly infected high-skill (T_t^h) and low-skill (T_t^l) workers are then given by

$$\begin{aligned} T_t^h &= \pi_{s1}(S_t^h C_t^{S,h})(I_t C_t^I) + \pi_{s2}(S_t^h N_t^{S,h})(I_t N_t^I) + \pi_{s3} S_t^h I_t, \\ T_t^l &= \pi_{s1}(S_t^l C_t^{S,l})(I_t C_t^I) + \pi_{s2}(S_t^l N_t^{S,l})(I_t N_t^I) + \pi_{s3} S_t^l I_t. \end{aligned}$$

The infection rates among the high-skill (τ_t^h) and low-skill (τ_t^l) workers are defined as $\tau_t^h = T_t^h / S_t^h$ and $\tau_t^l = T_t^l / S_t^l$ respectively. The evolution of the susceptible population for both high and low skill workers are given by

$$\begin{aligned} S_{t+1}^h &= S_t^h - T_t^h, \\ S_{t+1}^l &= S_t^l - T_t^l. \end{aligned}$$

Upon getting infected, people can move out of the infection pool either because of their recovery or death. Let π_r and π_d denote the probability of recovery and death conditional on being infected. The evolution of the infected population is

$$\begin{aligned} I_{t+1}^h &= I_t^h + T_t^h - (\pi_r + \pi_d) I_t^h, \\ I_{t+1}^l &= I_t^l + T_t^l - (\pi_r + \pi_d) I_t^l. \end{aligned}$$

$\pi_r I_t^h$ and $\pi_r I_t^l$ refers to the total number of recovered high and low-skill workers while $\pi_d I_t^h$ and $\pi_d I_t^l$ denotes the total number of people who die. The law of motion for recov-

[3] Total onsite labour of all infected population is given by $(I_t N_t^I) = I_t^h N_t^{I,h} + I_t^l N_t^{I,l}$

ered people is given by

$$R^h_{t+1} = R^h_t + \pi_r I^h_t,$$
$$R^l_{t+1} = R^l_t + \pi_r I^l_t,$$

while that for the dead follows

$$D^h_{t+1} = D^h_t + \pi_d I^h_t,$$
$$D^l_{t+1} = D^l_t + \pi_d I^l_t.$$

The population of high and low-skill workers evolves according to

$$pop^h_{t+1} = pop^h_t - \pi_d I^h_t,$$
$$pop^l_{t+1} = pop^l_t - \pi_d I^l_t.$$

At the initial period, we assume ϵ fraction of total population are infected. The total number of high-skill and low-skill workers infected at period zero is

$$I^h_0 = \psi\epsilon, \qquad I^l_0 = (1-\psi)\epsilon,$$

and the total susceptible population at the initial period is

$$S^h_0 = \psi(1-\epsilon), \qquad S^l_0 = (1-\psi)(1-\epsilon).$$

All agents in the economy take these laws of motion as given and make their economic decisions. We describe the decision problems of different agents below.

2.2.1 Susceptible People

High-skill (and similarly low-skill) susceptible workers choose their consumption, on-site and remote labour to maximize their lifetime utility

$$U_t^{s,h} = u(c_t^{s,h}, n_t^{s,h}, \hat{n}_t^{s,h}) + \beta\Big[(1-\tau_t^h)U_{t+1}^{s,h} + \tau_t^h U_{t+1}^{i,h}\Big],$$

subject to the budget constraint

$$c_t^{s,h} = w_t^h\Big((1-\mu_t)n_t^{s,h} + \eta^h \hat{n}_t^{s,h}\Big) + \Gamma_t^h,$$

τ_t^h, the infection rate of high-skill workers, is given by

$$\tau_t^h = \pi_{s1}c_t^{s,h}(I_t C_t^I) + \pi_{s2}n_t^{s,h}(I_t N_t^I) + \pi_{s3}I_t.$$

Susceptible people take the aggregate consumption $(I_t C_t^I)$ and onsite labour $(I_t N_t^I)$ of infected population as given while making their decisions. Assuming the flow utility function as $u(c_t^{s,h}, n_t^{s,h}, \hat{n}_t^{s,h}) = log(c_t^{s,h}) - \frac{\theta}{2}(n_t^{s,h})^2 - \frac{\hat{\theta}}{2}(\hat{n}_t^{s,h})^2$, the first order conditions are:

$$\begin{aligned}
\frac{1}{c_t^{s,h}} - \lambda_t^{s,b} + \lambda_t^{\tau}\pi_{s1}(I_t C_t^I) &= 0,\\
-\theta n_t^{s,h} + \lambda_t^{s,b} w_t^h(1-\mu_t) + \lambda_t^{\tau}\pi_{s2}(I_t N_t^I) &= 0,\\
-\hat{\theta}\hat{n}_t^{s,h} + \lambda_t^{s,b} w_t^h \eta^h &= 0,\\
\beta[U_{t+1}^{i,h} - U_{t+1}^{s,h}] &= \lambda_t^{\tau},
\end{aligned}$$

where $\lambda_t^{s,b}$ and λ_t^{τ} denotes the Lagrange multipliers of budget constraint and infection rate respectively. The optimization problem of a low-skill worker is exactly analogous to the above mentioned problem.

2.2.2 Infected People

A high-skill infected person maximizes

$$U_t^{i,h} = u(c_t^{i,h}, n_t^{i,h}, \hat{n}_t^{i,h}) + \beta\Big[(1-\pi_r-\pi_d)U_{t+1}^{i,h} + \pi_r U_{t+1}^{r,h}\Big],$$

subject to the budget constraint

$$c_t^{i,h} = w_t^h \left(\phi(1-\mu_t) n_t^{i,h} + \eta^h \hat{\phi} \hat{n}_t^{i,h} \right) + \Gamma_t^h.$$

Parameters ϕ and $\hat{\phi}$ captures the loss in onsite and remote labour productivity due to getting infected.[4] Assuming the same utility function as before, the first order conditions are

$$\begin{aligned}
\frac{1}{c_t^{i,h}} - \lambda_t^{i,b} &= 0, \\
-\theta n_t^{i,h} + \lambda_t^{i,b} w_t^h \phi (1-\mu_t) &= 0, \\
-\hat{\theta} \hat{n}_t^{i,h} + \lambda_t^{i,b} w_t^h \hat{\phi} \eta^h &= 0,
\end{aligned}$$

where $\lambda_t^{i,b}$ is the Lagrange multiplier of the budget constraint.

2.2.3 Recovered People

A high-skill recovered person maximizes the lifetime utility

$$U_t^{r,h} = u(c_t^{r,h}, n_t^{r,h}, \hat{n}_t^{r,h}) + \beta U_{t+1}^{r,h},$$

subject to the budget constraint

$$c_t^{r,h} = w_t^h \left((1-\mu_t) n_t^{r,h} + \eta^h \hat{n}_t^{r,h} \right) + \Gamma_t^h.$$

The first order conditions are given by

[4] One interpretation is that a fraction ϕ ($\hat{\phi}$) of the infected individuals are too sick to provide onsite (remote) labour.

$$
\begin{aligned}
\frac{1}{c_t^{r,h}} - \lambda_t^{r,b} &= 0, \\
-\theta n_t^{r,h} + \lambda_t^{r,b} w_t^h (1-\mu_t) &= 0, \\
-\hat{\theta}\hat{n}_t^{r,h} + \lambda_t^{r,b} w_t^h \eta^h &= 0.
\end{aligned}
$$

with $\lambda_t^{r,b}$ being the Lagrange multiplier of the budget constraint.

2.2.4 Market Clearing

In equilibrium, both goods and labour markets clear as follows.

Labour Market:

$$
\begin{aligned}
S_t^h\Big((1-\mu_t)n_t^{s,h} + \eta^h \hat{n}_t^{s,h}\Big) + I_t^h\Big(\phi(1-\mu_t)n_t^{i,h} + \eta^h \hat{\phi}\hat{n}_t^{i,h}\Big) + R_t^h\Big((1-\mu_t)n_t^{r,h} + \eta^h \hat{n}_t^{r,h}\Big) &= L_t^h, \\
S_t^l\Big((1-\mu_t)n_t^{s,l} + \eta^l \hat{n}_t^{s,l}\Big) + I_t^l\Big(\phi(1-\mu_t)n_t^{i,l} + \eta^l \hat{\phi}\hat{n}_t^{i,l}\Big) + R_t^l\Big((1-\mu_t)n_t^{r,l} + \eta^l \hat{n}_t^{r,l}\Big) &= L_t^l, \\
\left[\gamma^{1/\delta}(L_t^h)^{\frac{\delta-1}{\delta}} + (1-\gamma)^{1/\delta}(L_t^l)^{\frac{\delta-1}{\delta}}\right]^{\frac{\delta}{\delta-1}} &= L_t.
\end{aligned}
$$

Goods Market:

$$
\begin{aligned}
S_t^h c_t^{s,h} + I_t^h c_t^{i,h} + R_t^h c_t^{r,h} &= C_t^h, \\
S_t^l c_t^{s,l} + I_t^l c_t^{i,l} + R_t^l c_t^{r,l} &= C_t^l, \\
C_t^h + C_t^l &= AL_t.
\end{aligned}
$$

3. Calibration

In this section, we discuss the calibration of all the parameters of the model. We have two sets of parameters: (1) economic and (2) disease. The first set consists of the share of high-skill occupations, ψ, the elasticity of substitution between onsite and remote labour for both high-skill and low-skill occupations, η^h and η^l, the high-skill occupation productivity premium, γ, the elasticity of substitution between high and low-skill occupations, δ, the productivity of infected people when providing market and remote labour, ϕ and $\hat{\phi}$, the dis-utility of onsite and market labour, θ and $\hat{\theta}$, the discount factor, β, and the economy-wide TFP, A. The second set consists of the probability of recovery, π_r, the probability of death, π_d, the transmission probabilities from consumption, market labour and social interactions, π_1, π_2 and π_3, and the initial share of infected individuals in the economy, ϵ.

3.1 Economic parameters

Determination of ψ, η^h, η^l: The National Classification of Occupation - 2015 (NOC-2015) considers nine broad occupation categories and associates a skill level with each of these occupations. In this classification, an "occupation" is a set of jobs with similar tasks while "skill" is the ability to carry out those tasks.[5] NCO-2015 categorises four skill levels based on formal and informal education levels. These are (i) Primary education (upto 10 years of formal education and/or informal skill), (ii) Secondary education (11-13 years of formal education), (iii) First university degree (14-15 years of formal education), and (iv) Post-graduate university degree (more than 15 years of formal education). The occupations and the associated skill levels are presented in Table 1. We group the two highest skill levels into a high-skill (h) category, and the rest to a low-skill (l) category. Accordingly, occupation codes 1 - 3 in Table 1 correspond to high-skill occupations while codes 4-5 and 7-9 correspond to low-skill occupations. The share of high-skill occupations, ψ, comes out to be 20 percent.

In Table 1, we also report η for each occupation. This is the reduction in effective labour supply when a high-skill (low-skill) worker substitutes one unit of onsite labour with one unit of remote labour. We obtain an estimate of this parameter from Saltiel (2020). In a recent paper, Saltiel computes the share of workers in different occupations who can work remotely. He looks at 10 developing countries and finds that these "remote work" shares are surprisingly stable across countries. Accordingly, we use the

[5] https://www.ncs.gov.in/Documents/National%20Classification%20of%20Occupations%20_Vol%20II-A-%202015.pdf

Table 1: Occupations and Skills

NOC codes	Title	Skill	Share	η
1	Legislators, Senior Officials, and Managers	IV	0.102	0.34
2	Professionals	IV	0.052	0.34
3	Associate Professionals	III	0.046	0.27
4	Clerks	II	0.032	0.42
5	Service Workers and Sales Workers	II	0.112	0.06
7	Craft and Related Trades Workers	II	0.184	0.03
8	Plant and Machine Operators and Assemblers	II	0.072	0.00
9	Elementary Occupations	I	0.400	0.02

Note: The NOC codes refer to divisions, the most aggregated categories. The skill levels are I: Primary Education, II: Secondary Education, III: First University Degree, IV: Post-Graduate University Degree. The skill classification for division 1 in NOC-15 is actually not defined because of the large variation in tasks of these occupations. We assign it the highest skill level, but perform robustness with respect to the assignment. Division 6 (Skilled Agricultural and Fishery Workers) has been excluded from the analysis. Share refers to the share of the occupation in the total workforce. η is the share of individuals in an occupation who can work remotely.
Source: National Sample Survey (NSS) 2011-12 for occupation shares, Government of India's Ministry of Labour and Employment for NOC codes and associated skills, Saltiel (2020) for remote work shares.

average value of the remote work shares in Saltiel (2020) as our measure of η.[6] The occupations he looks at are the same as the NOC occupations that we consider, allowing a simple mapping between his and our measures. Using the occupation weights then gives us $\eta^h = 0.32$ and $\eta^l = 0.04$.

Determination of γ: γ has implications for the relative wage between high and low skill workers. We calibrate γ to be 0.70 to match the pre-pandemic wage ratio (w^h/w^l) of 4.34.[7]

[6]Our reasoning is as follows: Suppose only a fraction η of individuals in any occupation can work remotely. Then if aggregate supply of onsite labour is 1 (normalized), the aggregate supply of remote labour is simply η. Hence, one unit of onsite labour is equivalent to η units of remote labour.

[7]Based on International Labour Organization's India Wage Report (2018).

Determination of δ: In line with the findings documented in Acemoglu and Autor (2011), we set the elasticity of substitution between high and low skill workers, δ to be 1.5.

Determination of θ, $\hat{\theta}$: We set $\theta = \hat{\theta} = 0.034$ to target a pre-pandemic daily labour supply of 5 hours of onsite work and around 1.5 hours of remote work for high-skill workers.

Determination of ϕ, $\hat{\phi}$: We set $\phi = \hat{\phi} = 0.8$. The argument is that a certain proportion of infected workers will be too sick to work. This proportion could, of course, be different for onsite and remote work.

Determination of β and A: We choose $\beta = (0.96)^{1/365}$ so that each model period corresponds to a day. We also set the total factor productivity $A = 65.12$ to target a pre-pandemic average daily income of 235 Indian Rupees (INR).

3.2 Disease parameters

Value for π_r, π_d : In every period, a fraction of the infected individuals change status, i.e., they either recover or die. We refer to them as "closed" cases. The probability that an infected person dies in a period, π_d, is then given by

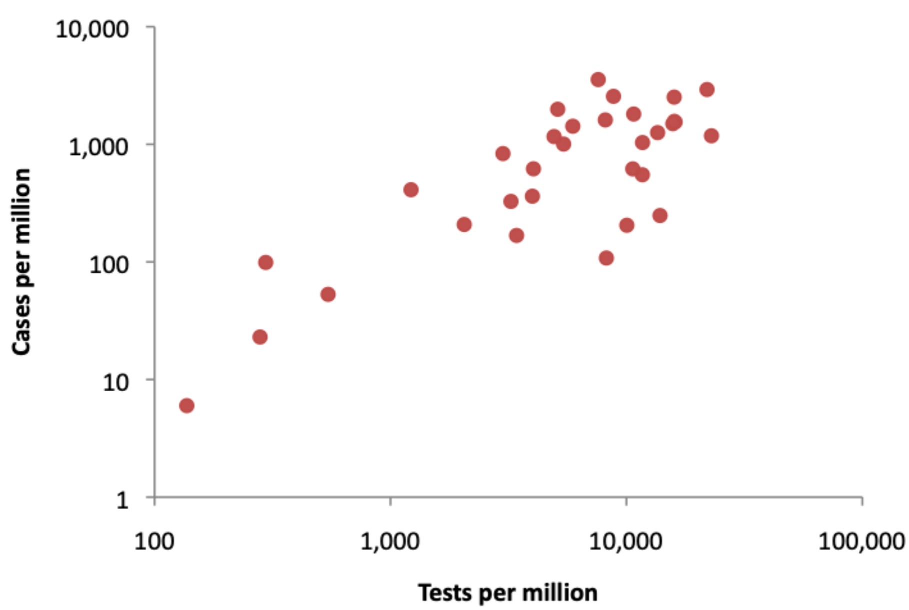
$$\pi_d = m \times Pr(closed),$$

where m, the mortality rate, measures the fraction of closed cases who have died, while $Pr(closed)$ is the probability of a case getting closed.

Evidence from China (WHO, 2020) suggests that for Covid-19, it takes about 2 weeks on average from onset to clinical recovery for mild cases, while the corresponding number for patients with severe or critical disease is 4.5 weeks. The same report suggests that among the people who were found to be infected, around 80 percent exhibited mild to moderate symptoms. So, the expected time taken by an infected individual to recover is 2.5 weeks or roughly 18 days. Assuming that 18 days is also the expected time taken by an infected individual to die (the range is 2-6 weeks), the probability of a case closing in one day is 1/18.

Computing, m, the mortality rate poses some challenges. If the pandemic ends at period T, the mortality rate is measured by D_T/I_T, because the number of infections will eventually be equal to the number of closed cases. There are, however, two problems with this measure, one of which leads to a downward bias while the other one leads to an upward bias. To illustrate the first problem, suppose we had data on a historical pandemic episode. Because we are looking at a historical episode, it would be safe to assume that every infected individual either recovered or died. Then the mortality rate would simply be the number of final deaths divided by the total number of infected. During an ongoing pandemic, we cannot make this assumption. So, even if there are no new infections, in which case the number of infections necessarily equals the number of closed cases, the number of deaths could still go up. Accordingly, the mortality measure could be biased downward.

Figure 1: Positive cases and testing for Covid-19 in a cross-section of countries



Note: Figures are current as of 12th April, 2020.
Source: www.worldometers.info

A more serious problem with looking at the ratio of deaths to infected is that the latter value could be an under-estimate of the true value. This is because not every infected individual gets tested. In fact, the infection rate (infected/population) is strongly correlated with the testing rate (tests/population) as Figure 1 suggests. We can understand this problem as follows. The total number of infected individuals at time t (ignoring high versus low-skilled) can be written as

$$I_t = I_t^{test} + I_t^{notest},$$

where I_t^{test} and I_t^{notest} denote the number of infected individuals who have been tested and not tested respectively. We can re-write the above equation as

$$I_t = \frac{1}{1-a} I_t^{test},$$

where $a = I_t^{notest}/I_t$ is the ratio of infected individuals who do not get tested. Of course, we do not know the value of a. But we might be able to offer an educated guess. One assumption is that because testing is a choice, infected individuals who are asymptomatic are more likely to not get tested. In that case, one way to approximate a is to use the asymptomatic rate. Preliminary studies suggest that the percentage of people with asymptomatic or mild symptoms is around 80 percent.[8] In India, there is reason to believe that this number could be higher due to the unavailability of test kits, at least in the early stages of the pandemic.[9] In light of these considerations, we choose a value of a equal to 0.9. As of 12th April, $I_t^{test} =$ 9,100 and $D =$ 300. With $a =$ 0.9, $I_t =$ 91,000. The mortality rate is then equal to 0.33 percent.[10] Accordingly,

$$\pi_d = 0.0033 \times 1/18 = 0.0002,$$

and

$$\pi_r = 1/18 - \pi_d = 0.0553.$$

Value for $\pi_{s1}, \pi_{s1}, \pi_{s3}$: In a standard SIR model, susceptible people get infected when

[8] www.ecdc.europa.au

[9] www.indiatoday.in

[10] Evidence from some of the most affected countries suggests that the mortality rate varies across age groups, with older populations displaying higher mortality rates.

they come in contact with infected people. The number of new infections in the population through such "social" interactions can be written as

$$T_t = \chi(S_t/P)I_t,$$

where χ is the transmission rate and P is the total population. χ measures the expected number of individuals who can get infected in time t by someone who is *already infected*. Observe that out of these χ individuals, only a fraction (S_t/P) will be new infections (assuming that infected individuals come in contact with other individuals randomly). Hence, the expected number of new infections created by an existing infected individual is $\chi(S_t/P)$. Multiplying by I_t, we get the total number of new infections. χ/P is known as the transmission probability.

In this paper, we assume that the transmission probabilities due to consumption, work and social interactions add up to χ/P. To get a value for χ, one can use the following relation:

$$R_0 = \chi/(\pi_r + \pi_d),$$

where R_0, the basic reproduction number, is the expected number of individuals who will be infected by a single infected individual over the course of the disease.[11] There are a number of studies looking at the R_0 for Covid-19 (Wang et al., 2020). We use $R_0 = 2.2$, which is in the mid-range of R_0 across these studies. Because P has been normalized to one, this gives us $\chi/P = 2.2 \times 0.0555 \approx 0.12$. At the beginning of a pandemic, we then have

$$\pi_{s1} \times C^2 + \pi_{s2} \times N^2 + \pi_{s3} = 0.12,$$

where C and N are the pre-pandemic equilibrium values for consumption and onsite labour respectively. How do we allocate the transmission probability across the different ways individuals can get infected? One possibility is to look at how much time Indians spend on different activities. Time-Use Survey data (1999) suggests that an average Indian spends 68 hours per week outside home. Out of these, around 35 hours

[11] $R_0 = \chi + (1 - \pi_r - \pi_d)\chi + (1 - \pi_r - \pi_d)^2\chi + \ldots.$

are spent on work, 2 hours are spent on consumption-related market activities and the rest on activities that could lead to social interactions. It follows that

$$\frac{\pi_{s1} \times C^2}{\pi_{s1} \times C^2 + \pi_{s2} \times N^2 + \pi_{s3}} = \frac{2}{68},$$

and

$$\frac{\pi_{s2} \times N^2}{\pi_{s1} \times C^2 + \pi_{s2} \times N^2 + \pi_{s3}} = \frac{35}{68}.$$

Solving, we have $\pi_1 = 6.5 \times 10^{-8}$, $\pi_2 = 0.0023$ and $\pi_3 = 0.0557$.

Value for ϵ : We assume that initially, a fraction 10^{-6} of the population was infected (this amounts to 1,300 individuals).

4. Results

In this section, we present and discuss the economic and health impacts of the spread of COVID-19. We measure the economic impact using aggregate output and consumption inequality between high-skill and low-skill workers. Consumption inequality is captured using relative consumption of high-skill with respect to low-skill workers (c_t^h/c_t^l).[12] We use peak infection rate and also the number of days it takes for the infections to double till the peak to measure health effects. Peak infection rates captures the maximum stress that the healthcare services might come under while the days to double measures the speed at which the infection transmits through the economy. We start with the benchmark case of no policy intervention. We follow it up by discussing different containment policies that the governments could implement and how it might exacerbate the already existing inequality. Finally, we talk about the optimal transfers designed to keep the inequality unchanged and its effect on health outcomes.

[12]The consumption inequality is calculated as the weighted average of relative consumption across the different cohorts i.e. susceptible, infected and recovered.

$$Inequality_t = \frac{S_t^l(c_t^{s,h}/c_t^{s,l}) + I_t^l(c_t^{i,h}/c_t^{i,l}) + R_t^l(c_t^{r,h}/c_t^{r,l})}{S_t^l + I_t^l + R_t^l}.$$

4.1 Benchmark (No Policy)

Figure 2 shows the propagation of the disease for both high and low skill workers under no policy intervention. Our simulations show that the infections peak on day 218 when around 15.5% of initial population will be infected, imposing massive stress on the healthcare facilities. The average daily growth rate of infections from day 100 till the day infections peak is 4.94%, which translates to infections doubling every 14.4 days. Eventually, around 78.7% of the population gets infected by this pandemic.

The economic impact of the pandemic can be seen in figure 3. The total loss of aggregate output during the peak infection period is around 5.41%. As can be seen from the figure, both high and low skill workers realize the risk of infection from onsite work and substitute towards more remote work. The disease transmission being similar for both high and low skill workers in our setup, there is a very small effect on consumption inequality, with inequality slightly reducing during the peak infection days. But as we show in the next section, the various containment policies implemented to reduce the spread of infection can adversely affect low-skill consumption compared to high-skill consumption and hence worsen the already existing inequality.

4.2 Containment with No Transfers

We now introduce four different containment policies measured by the containment rate (μ) as shown in figure 4 and analyse their impact on various economic and health outcomes. In the first policy called sustained containment, the government imposes a severe lockdown with a containment of 80% of onsite labour for a sustained period of 300 days. The second policy called intermittent containment is similar to the previous policy, except that the government allows intermittent relaxation of the lockdown.[13] The third policy called staggered containment starts with a severe lockdown for 75 days followed by gradual easing every 75 days thereafter. Finally, smooth containment is a policy where the containment closely follows the evolution of infections in the economy with the containment rate peaking at 80% on the day of peak infections.

[13] In our simulation lockdown is relaxed for 30 days after every 75 days. See figure 4 for the simulated path of containment.

Table 2: Containment with No Transfers

Policy	Loss of Output (%)	Change in Inequality (%)	Peak Infection (%)		Days to Double	
			High Skill	Low Skill	High Skill	Low Skill
Benchmark	5.41	-0.66	15.31	15.82	14.40	14.37
Sustained	73.01	21.05	9.27	12.77	19.20	17.86
Intermittent	57.31	16.23	9.82	13.65	16.56	16.65
Staggered	48.58	7.68	12.36	14.29	17.54	17.01
Smooth	24.70	3.07	11.36	14.39	14.04	14.49

Note: Loss of output refers to the total decline in aggregate output as a percentage of initial steady state over the period of 300 days (from day 101 to 400) when the containment policies are implemented. Change in consumption inequality measures the average change in relative consumption compared to the pre-pandemic inequality of 4.56 over the same period. Peak infection reports the maximum infection as a percentage of initial population for both high and low skill workers. Days to double measures the average number of days it takes for the infections to double. Average is calculated from day 100 to the day infection peaks.

The evolution of various economic and health outcomes resulting from sustained, staggered, intermittent and smooth containment policies are shown in figures 6, 8, 10 and 12 respectively. We measure the economic impact of various containment policies by measuring changes in aggregate output and consumption inequality. Total change in aggregate output and consumption inequality is measured as the average change with respect to the initial steady state over a period of 300 days (from day 101 to 400) when the containment policies are implemented.

Table 2 shows the simulated economic and health indicators across different containment policies. The number of people infected, without any policy intervention doubles every 14.4 days on average and causes around 5.4% decline in aggregate output. Out of the different policies considered, sustained lockdown generates the best gains on health front lowering the peak infection rates by around 6 pp. for high skill workers and 3 pp. for low skill workers. It also slows down the spread of disease by increasing the time it takes to double from 14.4 days to 19.2 days for high-skill and 17.9 days for low skill workers respectively. This policy also imposes the maximum cost on the economic front with aggregate output falling by about 73% and consumption inequality increasing by 21% compared to the pre-pandemic inequality of 4.56, during the time this policy is in place. Intermittent lockdown is less costly on the economic front compared to the sustained containment both in terms of loss of output and increase in inequality. Even though it does a good job of reducing the peak infection rates, it is not as effective in containing the spread of the pandemic compared to the sustained lockdown.

Staggered containment slows the spread of the disease by increasing the doubling time from 14.4 days to around 17.5 days for high-skill and 17 days for low-skill workers. But it is not very effective in reducing the peak infection rates. In comparison to the previous two cases, the policy of staggered containment imposes relatively less strain on the country's economy with aggregate output falling by 48.58% and average inequality increasing by 7.68%. Smooth containment inflicts minimum damage on the country's economy but it is not effective in slowing down the spread of infections.

While analysing the effects of different containment policies, two clear observations emerge. First, there is a clear trade-off between containing the infections and its effect on economic activity. Sustained lockdown, which is most effective in containing the pandemic, is also the most costly in terms of lost output and increased inequality. Similarly, smooth containment, which is relatively cheaper to implement, is not as effective in checking the disease spread.

Second, the low-skill workers are disproportionately affected on both economic and health outcomes compared to high-skill workers. As all containment measures impose a massive cost on onsite labour, both high-skill and low-skill workers substitute towards more remote work. But because onsite labour is significantly less substitutable in low skill compared to high skill occupations, the low-skill workers are adversely affected by containment policies compared to high-skill workers. This worsens the already existing inequality, with an increase of around 20% in cases of sustained and intermittent containment. Since remote labour is not very productive for low-skill workers, they optimally choose to provide more onsite labour compared to high-skill workers. This causes the containment policies to be less effective for low-skill workers leading to a higher incidence of infections among them. As can be seen, the sustained containment brings down the peak infection rates from 15.3% to 9.3% for high-skill but only to 12.8% for low-skill workers. Therefore in our setup, low-skill workers face an excessive burden on both economic and health fronts, with increased consumption inequality and higher incidence of infections compared to high-skill workers. In the next section, we show that conditional transfers can be designed to nullify the increase in inequality caused by various lockdown measures, and these transfers also improve the effectiveness of different containment policies.

4.3 Containment with Optimal Transfers

In this section we implement conditional transfers along with various lockdown policies to remedy the additional inequality generated by the different containment measures. These are conditional transfers as only low-skill workers, who are worse affected during lockdown receive them while the high-skill workers do not get any transfers ($\Gamma_t^h = 0$ for all t). The optimal transfer for low-skill workers (Γ_t^l) is chosen to bring the inequality back to pre-pandemic levels. Figure 5 shows the path of optimal transfers each low-skilled worker receives under different containment policies and figures 6, 8, 10 and 12 show the resulting inequality after the implementation of conditional transfers along with the different containment policies. As can be seen from these figures, the transfer policy is successful in reversing the increase in inequality across the different containment scenarios.

Table 3 shows the magnitude of transfers (as a percentage of GDP) required to remove the excess inequality under different containment policies. Figure 5 shows the optimal path of transfers in Indian Rupees (INR) allocated for each low-skilled worker. We obtain the total expenditure of this policy by aggregating these transfers over the entire non-agricultural low-skill workforce of 237 million workers obtained from World Bank data.[14,15] To put it in perspective, we represent this as a share of India's GDP, which

[14]Total labour force: https://data.worldbank.org/indicator/SL.TLF.TOTL.IN?locations=IN. Employment in agriculture: https://data.worldbank.org/indicator/SL.TLF.TOTL.IN?locations=IN. According to this data, the total labour force in India is 520 million, out of which the non-agricultural workforce is 296 million. Low-skill workers constitutes 80% of the non-agricultural labour, which amounts to 237 million.

[15]As of now we leave out the agricultural sector as the effect of different lockdown policies on agricul-

Table 3: Containment with Optimal Transfers

Policy	Loss of Output (%)	Transfers (% of GDP)	Peak Infection (%)		Days to Double	
			High Skill	Low Skill	High Skill	Low Skill
Benchmark	5.41	0	15.31	15.82	14.40	14.37
Sustained	73.98	0.29	8.73	10.34	23.28	22.15
Intermittent	58.04	0.29	8.85	11.08	20.16	19.37
Staggered	49.16	0.14	12.47	13.58	20.46	19.68
Smooth	24.89	0.06	11.27	13.37	14.19	14.31

Note: Loss of output refers to the total decline in aggregate output as a percentage of initial steady state over the period of 300 days (from day 101 to 400) when the containment policies are implemented. Total transfers are measured as a percentage of GDP. Peak infection reports the maximum infection as a percentage of initial population for both high and low skill workers. Days to double measures the average number of days it takes for the infections to double. Average is calculated from day 100 to the day infection peaks.

is around 200 trillion INR (approximately 2.65 trillion USD).

As can be seen from table 3, both sustained and intermittent containment policies generate large increases in inequality and hence require maximum transfers amounting to 0.29% of GDP. The staggered and smooth lockdown needs conditional transfers of around 0.14% and 0.06% of GDP respectively to take care of the excess inequality introduced by these policies. These conditional transfers should be considered as the minimum policy intervention needed to preserve the status-quo on inequality. Any containment policy affecting onsite labour without the accompanying transfers will compound the already existing problem of inequality.

Apart from reversing the excess inequality, conditional transfers also improves the effectiveness of various containment policies in controlling the spread of the pandemic. As can be seen from table 3, with conditional transfers in place, all the different lockdown measures yield much better results compared to a pure containment scenario. As shown in figures 7, 9, 11 and 13, the transfers received by low-skill workers enable

tural output is still not clear. For example, in the early phase of the lockdown, agricultural production seems to have been relatively less affected owing to robust demand for food items.

them to reduce their onsite labour and spend more time at their homes. In the case of sustained lockdown, onsite labour supply of low-skill workers goes down by just 4.7% when there are no transfers. But in the presence of transfers, the low-skill workers are able to reduce their onsite labour by 14.1%. This slows down the transmission of infections among the workforce and helps in containing the disease spread. As can be seen with transfers, the policy of sustained containment brings down the peak infection rate among low-skill workers from 15.8% to 10.34% compared to 12.77% in the pure containment case. Transfers also reduces the speed of disease transmission with infections taking 22.15 days to double compared to 17.86 days without transfers. This pattern of reduced peak infections and slowing down the disease spread holds for all the containment policies.

Even though the transfers are directed towards low-skill labour, the infections are better controlled among high-skill workers as well. More importantly, the conditional transfers aimed at limiting the increased consumption inequality also reduces the inequality on the health front by closing the gap in both peak infections and doubling days among high skill and low skill workers. Taking the case of sustained lockdown with transfers, the difference between high and low-skill peak infection rate is 1.61 pp. compared to 3.5 pp. without transfers. Similarly, transfers narrow the gap in the speed of transmission between high and low-skill workers.

Although the low-skill workers cut down on their labour supply, it does not increase the output loss by much. This is because of two opposing channels that positively affect output in the presence of transfers. One, containment along with transfers reduce the total number of infections in the economy. In the presence of transfers, around 69% of the people would eventually be infected due to this disease, compared to 72% in a pure containment case and 78% when no policy action is taken. Due to the reduction in number of infected people, the effective labour productivity is higher with transfers compared to the previous cases. Two, since the infection risk is reduced in the presence of transfers, the more productive high-skill workers choose to supply more onsite labour compared to the pure containment scenario. During the containment period with transfers, the reduction in high-skill onsite labour is around 49% compared to a

55% fall when there are no transfers, thus leading to increased production. These two effects compensate for the reduction in low-skill labour and mitigate any further loss in output.

These results show that conditional transfers should be an integral part of the policy toolkit along with containment policies in combating the pandemic. We find that a pure containment policy without accompanying transfers worsen the already existing inequality and is not effective in controlling the epidemic among low-skill workers. But implementing the optimal transfer policy designed to take care of the excess consumption inequality, apart from improving the effectiveness of various containment measures, also reduces the disparity in health outcomes between high and low-skill workers.

5. Conclusion

We integrate a standard epidemiological model within a general equilibrium framework to study the effect of pandemic and containment on high-skill and low-skill workers. We show that the different containment policies impose disproportionate economic costs on low-skill workers, thus worsening the already existing consumption inequality in the economy. On top of that, because low-skill workers do not have the luxury to work from home, the incidence of infections is also much higher compared to high-skill workers. We further show that, containment policies coupled with optimal transfers designed to take care of the excess inequality improves the performance of lockdown policies in controlling the disease spread and helps in reducing the disparity in health outcomes by discouraging the low-skill workers from venturing out for work.

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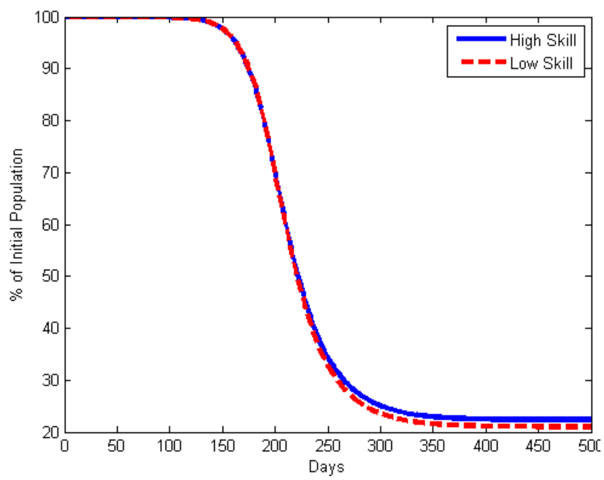
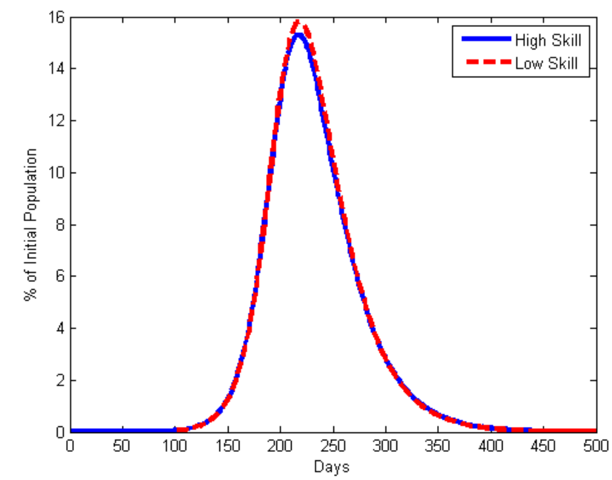
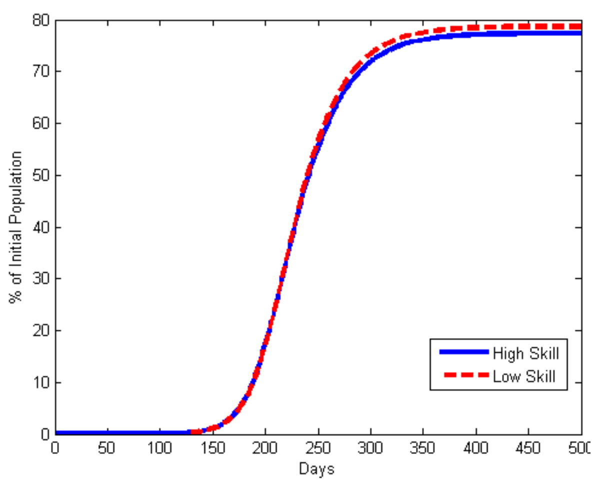


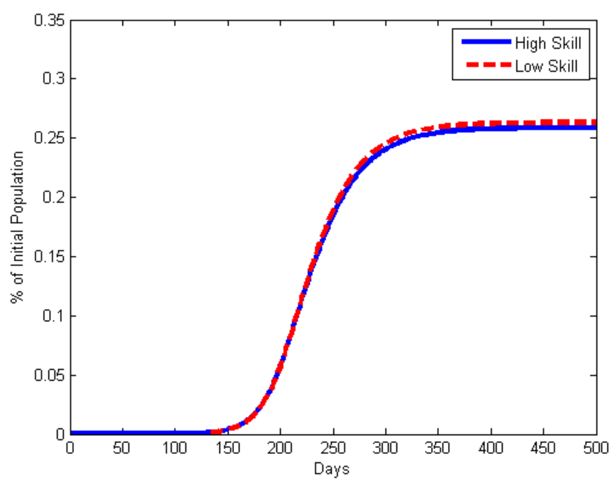
(a) Susceptibles



(b) Infected

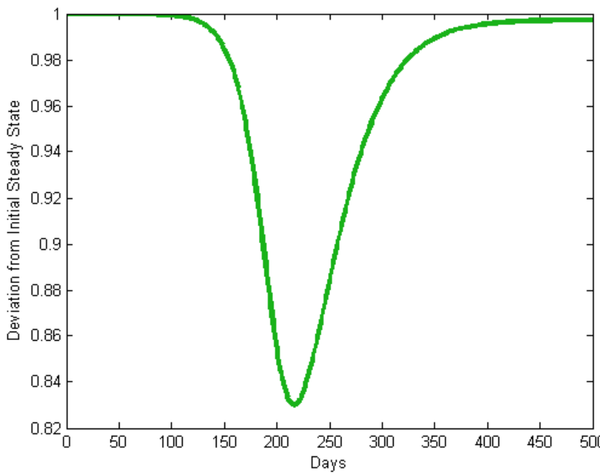


(c) Recovered

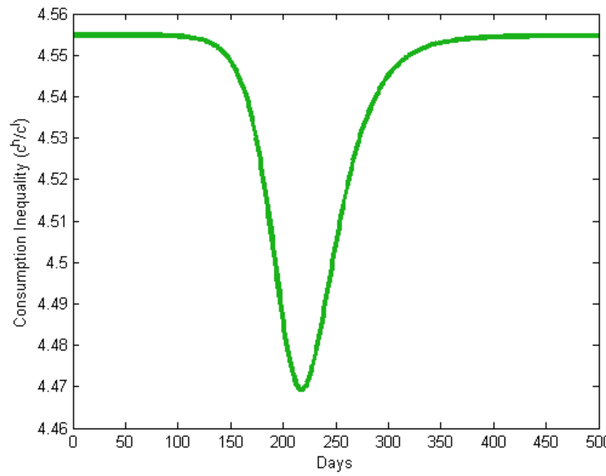


(d) Deceased

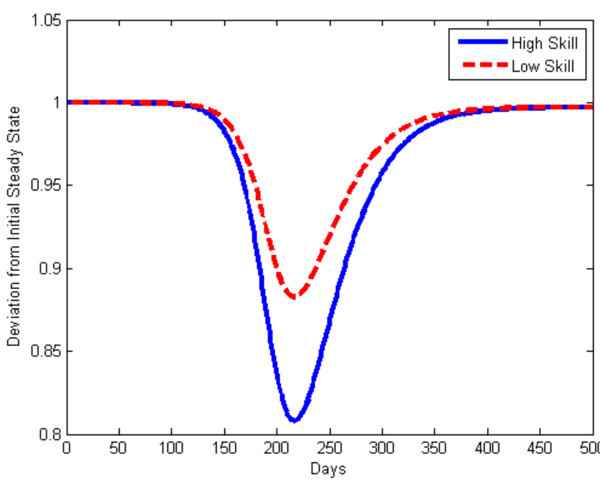
Figure 2: Disease Dynamics under No Policy



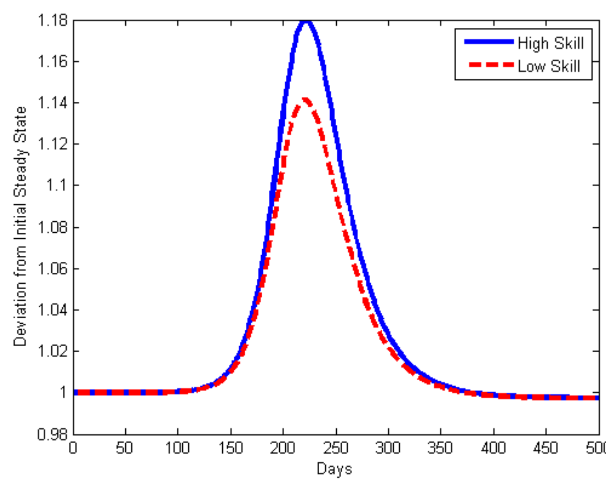
(a) Aggregate Output



(b) Consumption Inequality

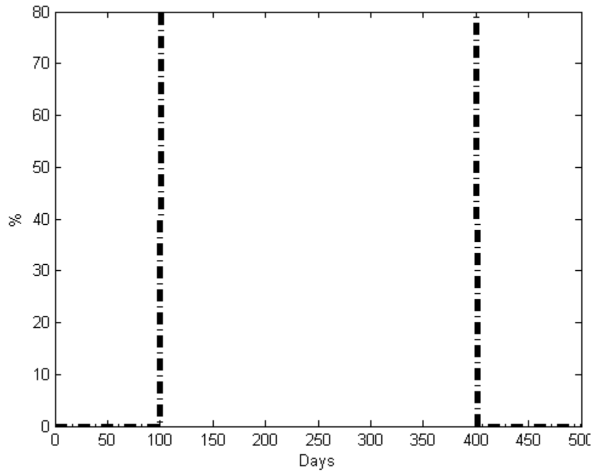


(c) Onsite Labour

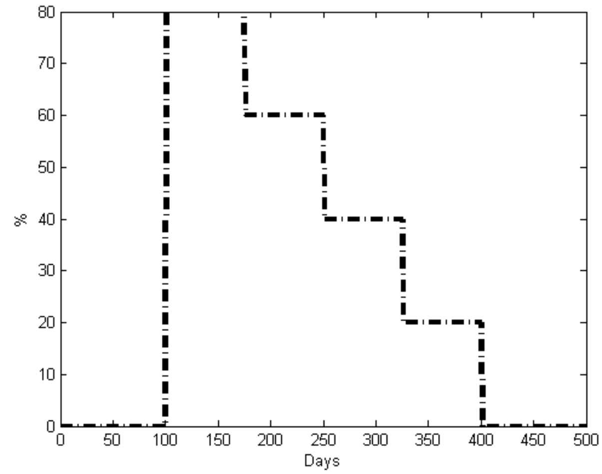


(d) Remote Labour

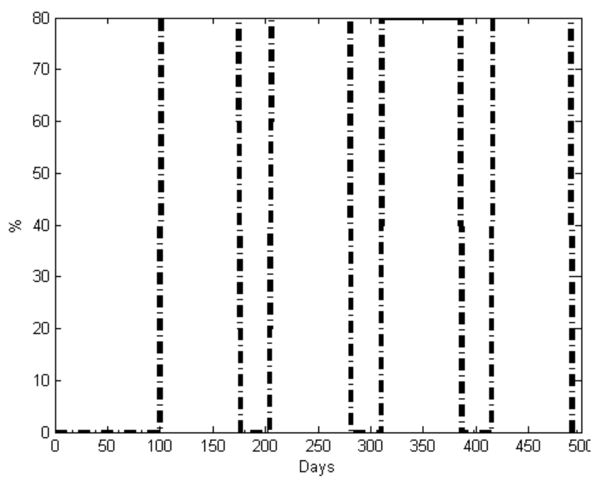
Figure 3: Economic Impact under No Policy



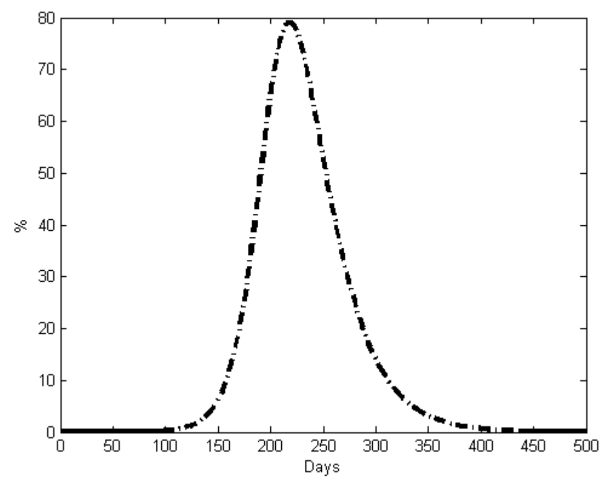
(a) Sustained Containment



(b) Staggered Containment

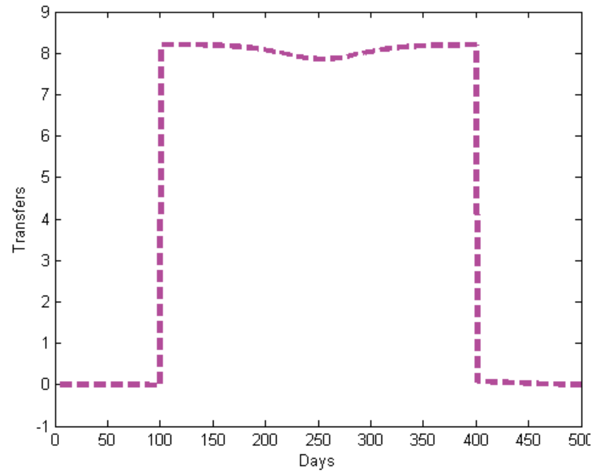


(c) Intermittent Containment

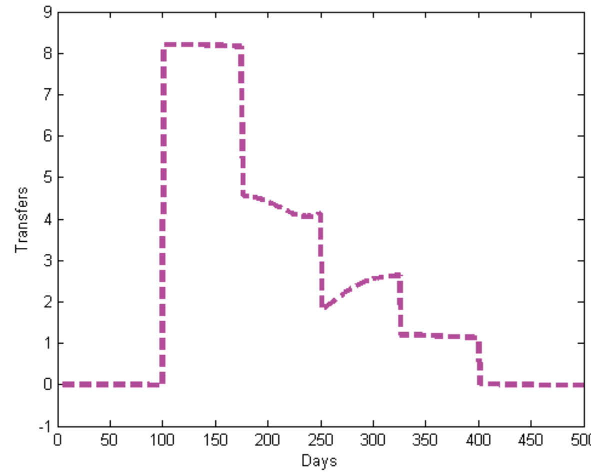


(d) Smooth Containment

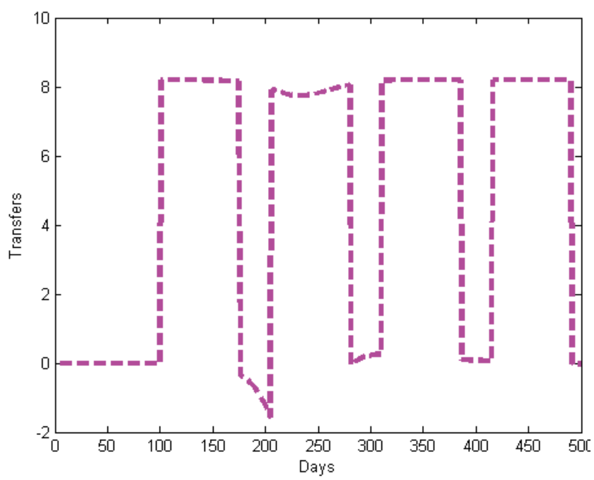
Figure 4: Containment Policies



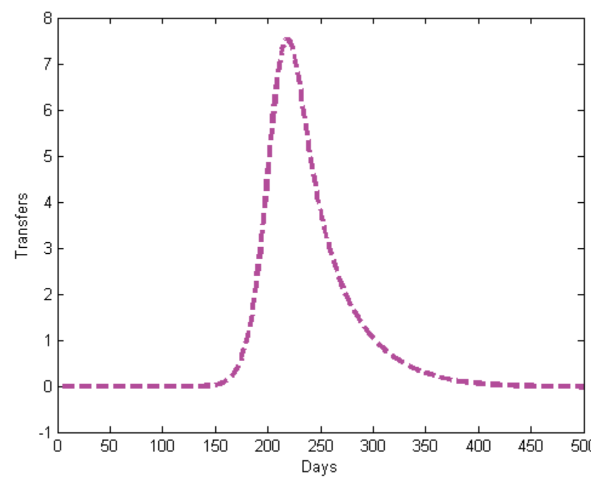
(a) Sustained Containment



(b) Staggered Containment

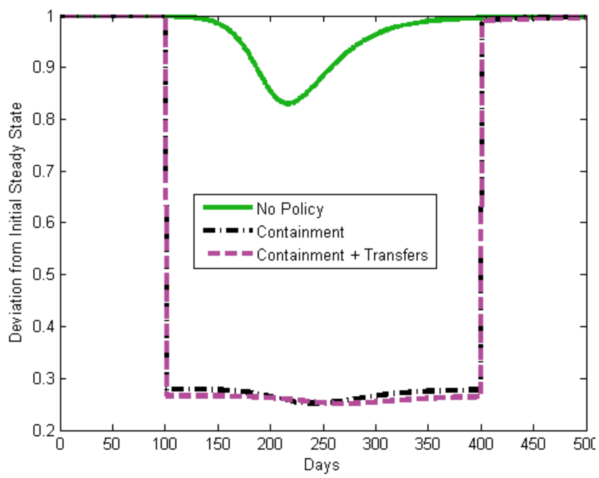


(c) Intermittent Containment

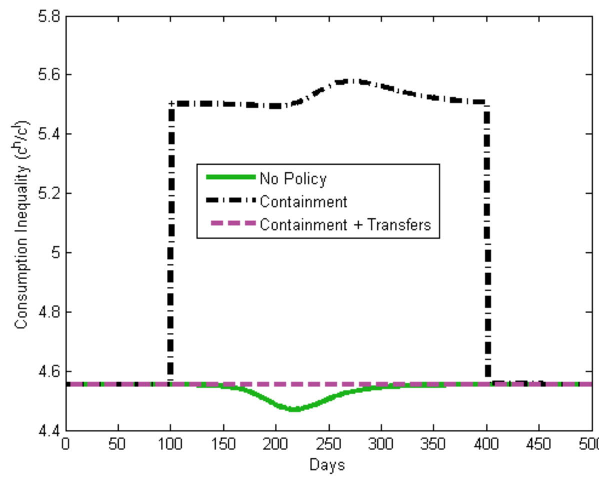


(d) Smooth Containment

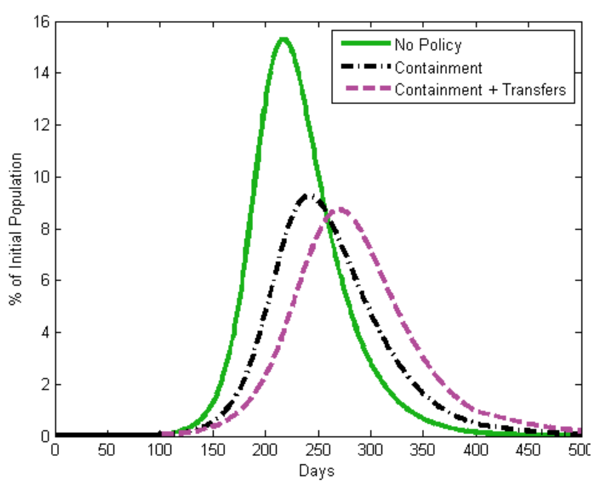
Figure 5: Optimal Transfers to Low Skill Workers



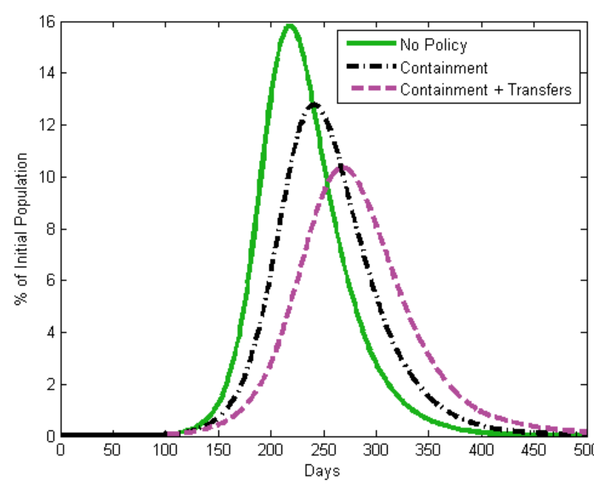
(a) Aggregate Output



(b) Consumption Inequality

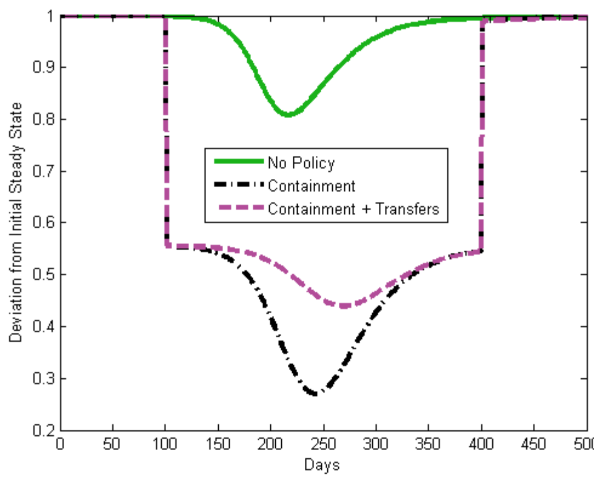


(c) High Skill Infections

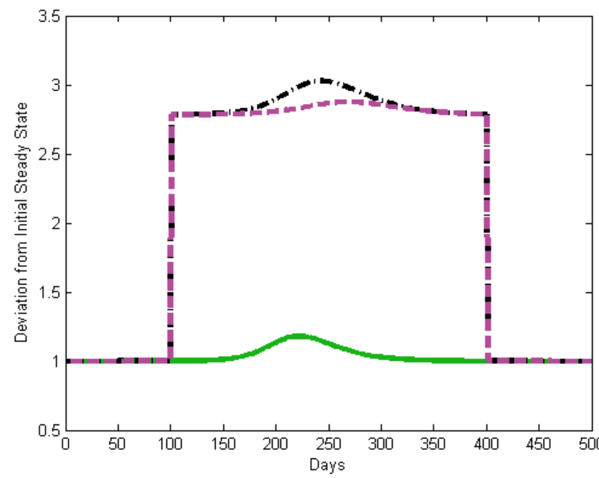


(d) Low Skill Infections

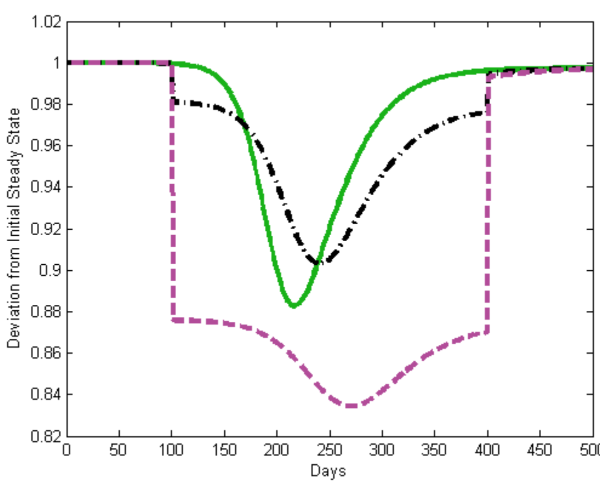
Figure 6: Sustained Containment



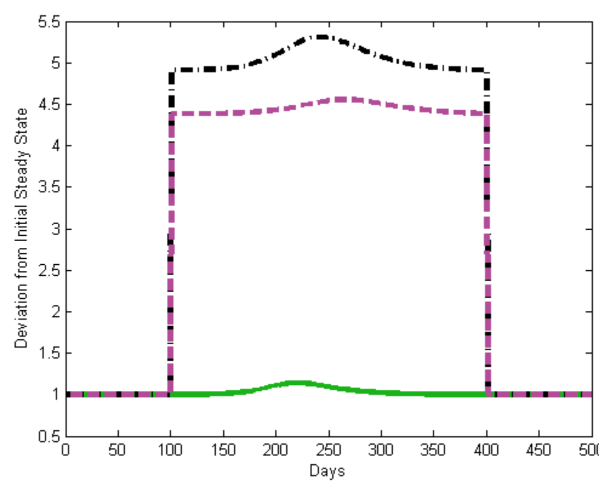
(a) High Skill Onsite Labour



(b) High Skill Remote Labour

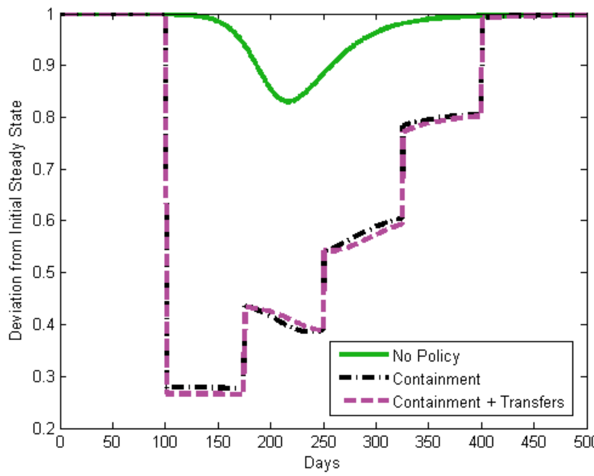


(c) Low Skill Onsite Labour

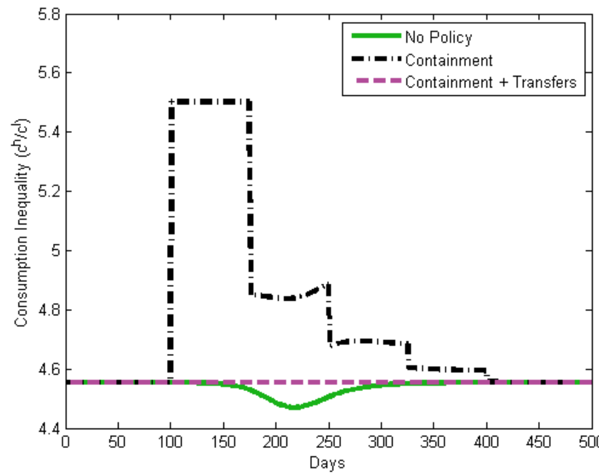


(d) Low Skill Remote Labour

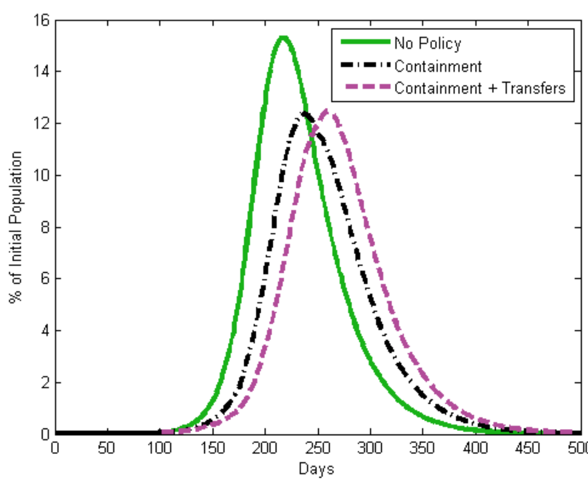
Figure 7: Sustained Containment



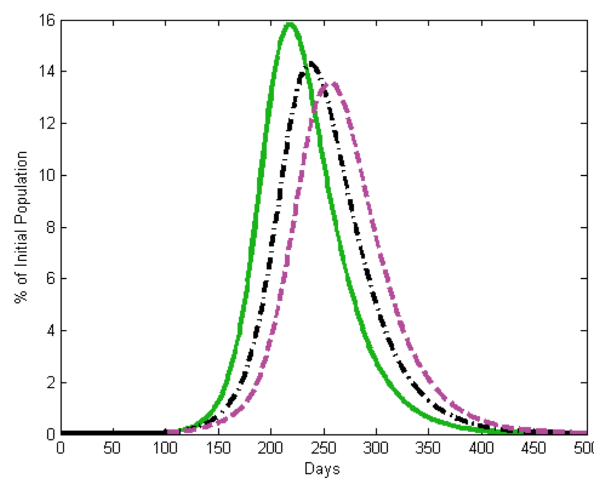
(a) Aggregate Output



(b) Consumption Inequality

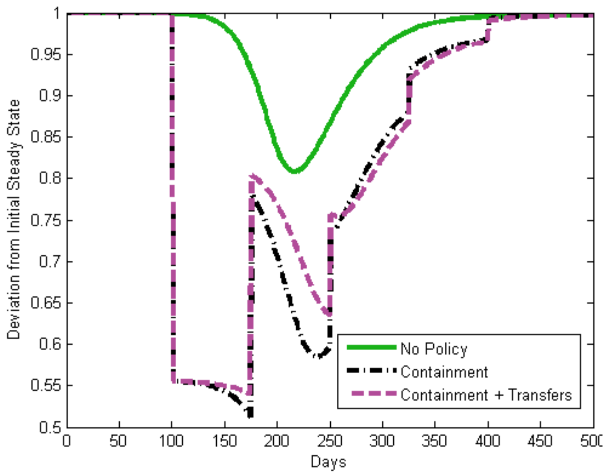


(c) High Skill Infections

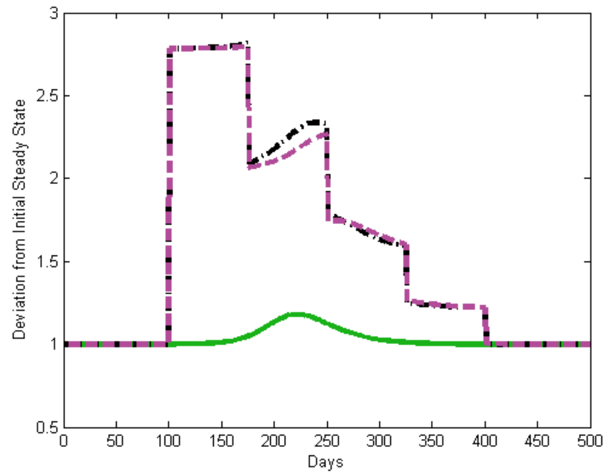


(d) Low Skill Infections

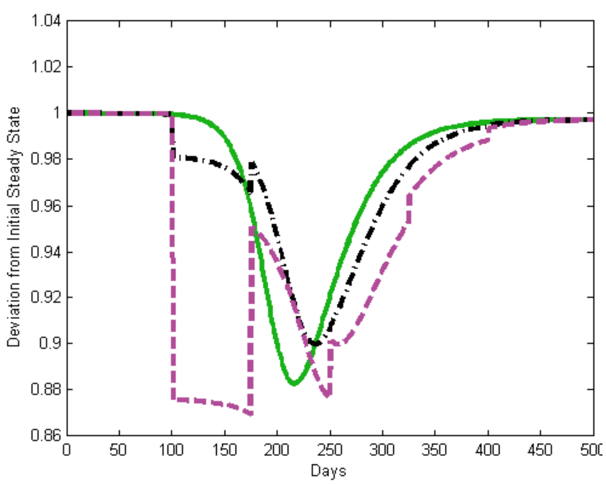
Figure 8: Staggered Containment



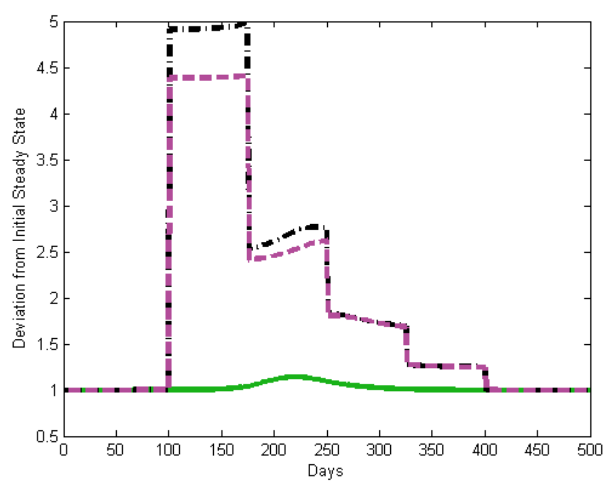
(a) High Skill Onsite Labour



(b) High Skill Remote Labour

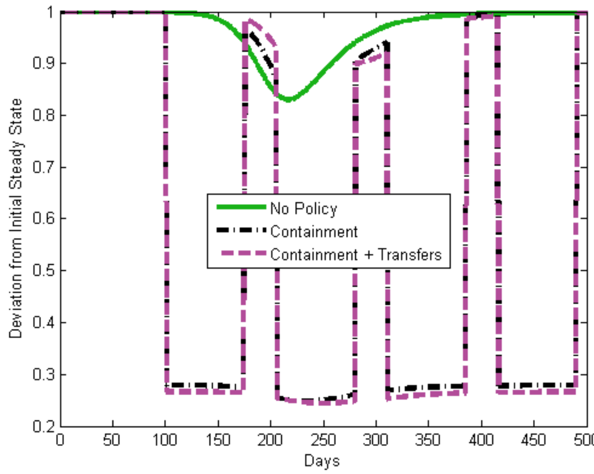


(c) Low Skill Onsite Labour

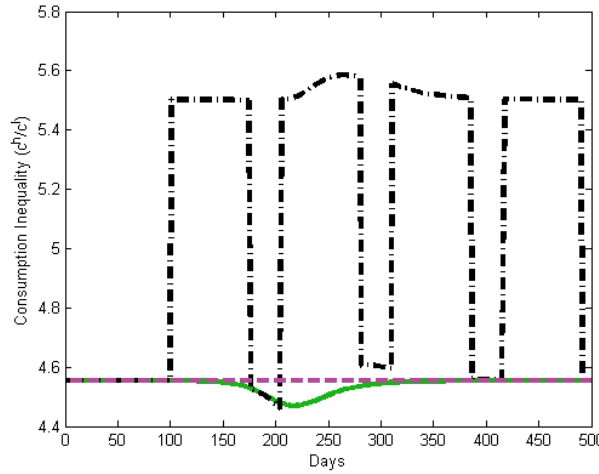


(d) Low Skill Remote Labour

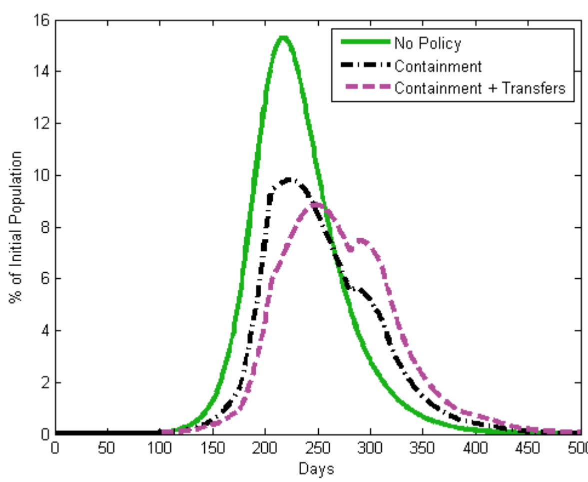
Figure 9: Staggered Containment



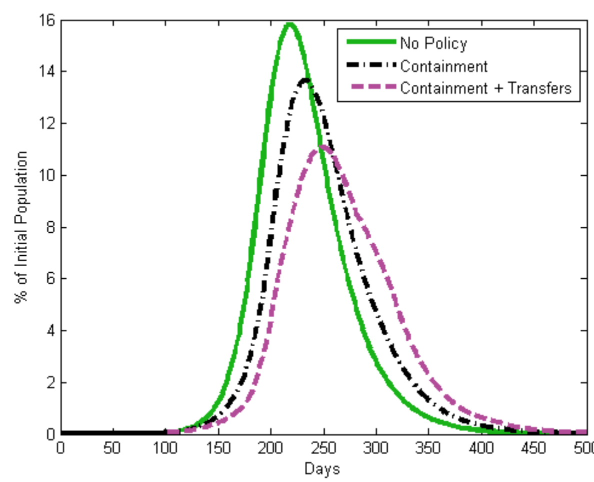
(a) Aggregate Output



(b) Consumption Inequality

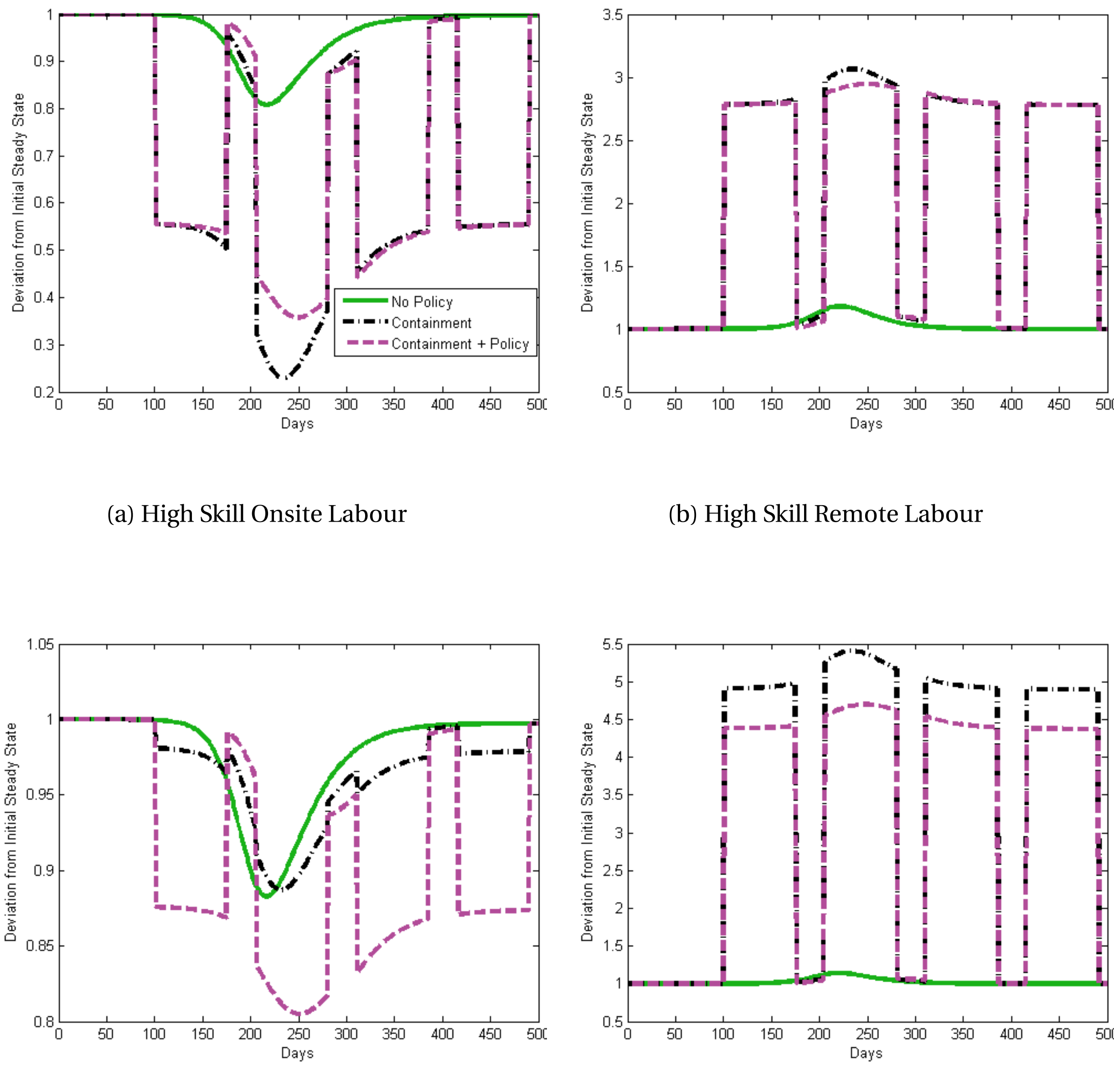


(c) High Skill Infections



(d) Low Skill Infections

Figure 10: Intermittent Containment



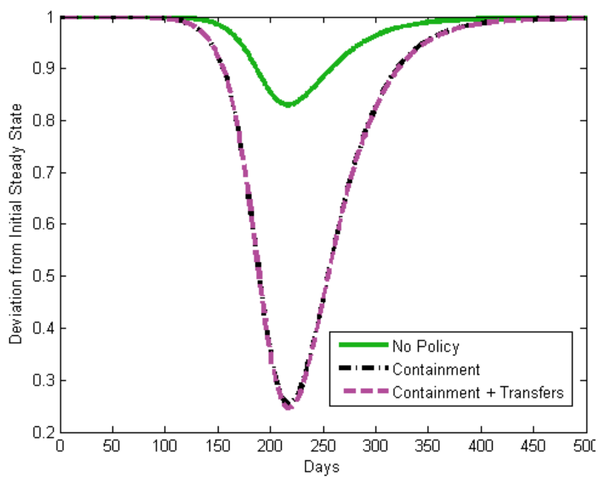
(a) High Skill Onsite Labour

(b) High Skill Remote Labour

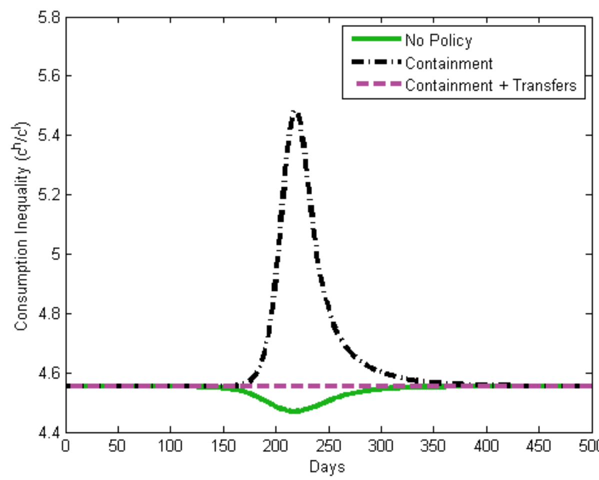
(c) Low Skill Onsite Labour

(d) Low Skill Remote Labour

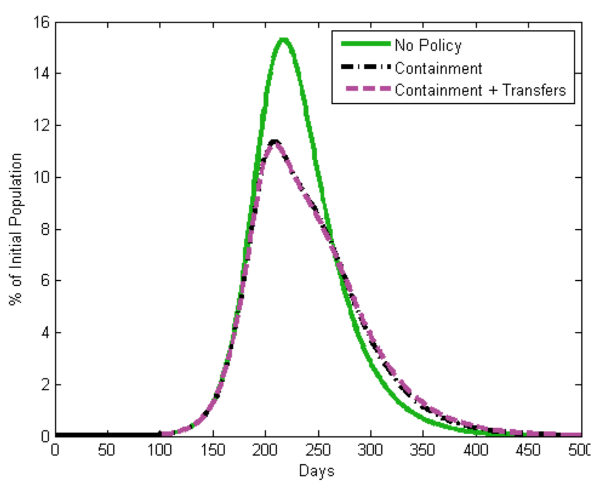
Figure 11: Intermittent Containment



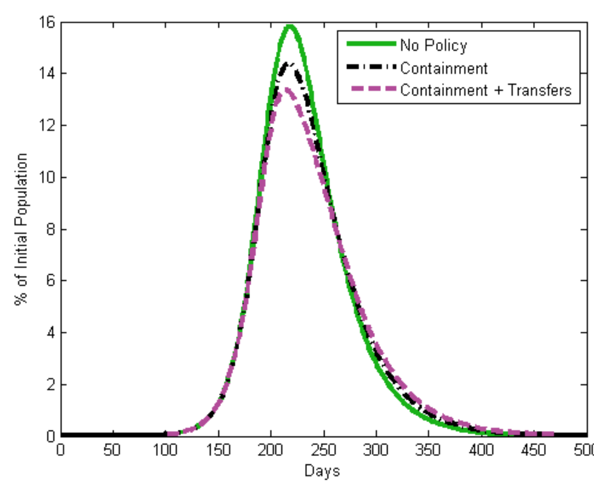
(a) Aggregate Output



(b) Consumption Inequality

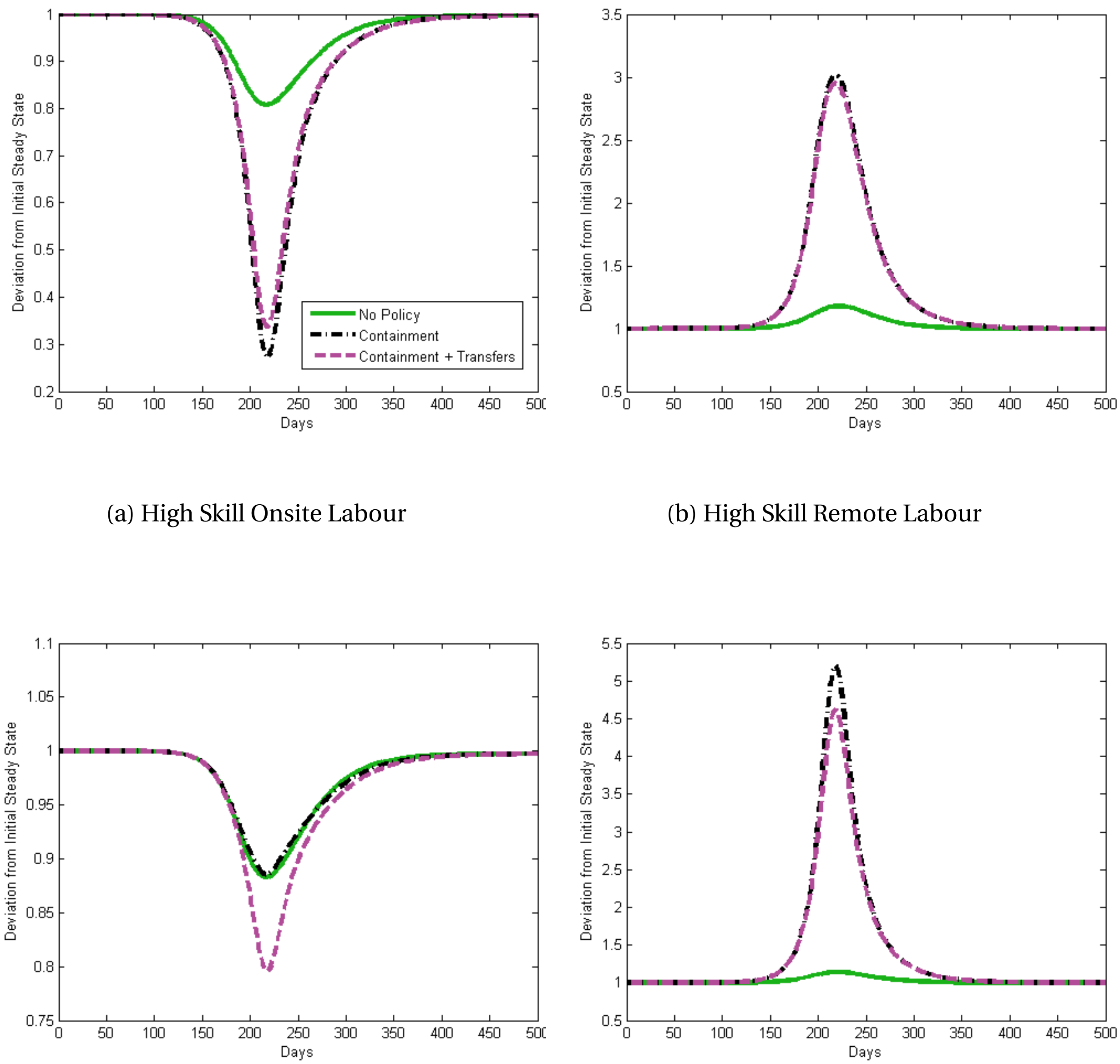


(c) High Skill Infections



(d) Low Skill Infections

Figure 12: Smooth Containment



(a) High Skill Onsite Labour

(b) High Skill Remote Labour

(c) Low Skill Onsite Labour

(d) Low Skill Remote Labour

Figure 13: Smooth Containment