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Pandemic Containment and Inequality in a Developing Economy

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Pandemic Containment and Inequality in a Developing Economy*

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Abstract

Using high frequency individual-level panel data from India, we show that income inequality, measured as the ratio of high-skilled to low-skilled income, increased sharply following the imposition of lockdown triggered by COVID-19. To explain this fact, we integrate a canonical SIRD epidemiological model into a general equilibrium framework with high-skilled and low-skilled 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-skilled relative to low-skilled workers. Upon introducing the containment policies calibrated to match the Indian experience, our model can explain between 24 and 60 percent of the observed increase in inequality. We also find that there is a higher incidence of infections among the low-skilled workers as they optimally choose to work more onsite compared to their high-skilled counterparts. Implementing direct transfers for low-skilled workers reverses this increase in inequality and improves the effectiveness of the containment policies.

JEL codes: E2, I1, J2.
Keywords: COVID-19, Containment, Inequality, Transfers.

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1. Introduction

With the global spread of COVID-19 pandemic, 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 effective social distancing, to the extreme, such as lockdowns. As entire sectors of the economy have stopped functioning due to these containment measures, the effect on average income has been devastating. In this paper, we argue that the various containment policies, apart from reducing average income, affects the income of low-skilled workers disproportionately compared to high-skilled workers, thus worsening the already existing income inequality.

Like numerous countries, India went into a lockdown during the early days of the pandemic. We use a high frequency individual-level panel data from India to document that income inequality, measured as the ratio of high-skilled to low-skilled income, increased sharply following the imposition of the lockdown. We find that introducing containment policies in a macroeconomic SIRD (Susceptible, Infected, Recovered, Dead) model calibrated to India, on top of capturing the empirical disease dynamics, can explain between 25 and 60 percent of the increase in income inequality depending on the calibration strategy. We go on to show that direct transfers targeted towards low-skilled workers can help in reversing this increased inequality and also improve the effectiveness of the containment policies in slowing down the pandemic.[1] Consequently, we argue in this paper that targeted transfers, in cash or kind, should be an integral component along with the containment policies to prevent worsening of inequality.

We obtain data on workers and their labour income from Consumer Pyramids Household Survey (CPHS). The CPHS is an individual level panel data of around 170,000 Indian households, containing information on worker income and consumption at a monthly frequency. Classifying workers into high-skilled and low-skilled based on their educational attainment, we find that the income inequality between these two

[1] There is a large literature documenting the positive impact of transfers on different economic outcomes. Fiszbein and Schady (2009) talks about its effect on poverty, Gertler (2004) discusses its impact on child health, and Galiani and McEwan (2013) on school enrollment, just to name a few.

groups of workers increased by around 38 percent between the months of March and June 2020, when the lockdown was implemented with maximum stringency. We also use data on infections to analyse the disease dynamics during the period when containment policies were in place.

In order to quantify the effect of COVID-19 containment policies on both economic as well as health outcomes, we embed a canonical SIRD epidemiological model into a dynamic, general equilibrium framework of production and consumption. In our model, production is carried out by two types of workers: high-skilled and low-skilled. At the forefront of our analysis are two observations: First, workers have the option of working either from their worksites or from their homes, with the labour supplied from their worksites (onsite labour) and the labour supplied from their homes (remote labour) being imperfect substitutes. Second, compared to low-skilled workers, the onsite labour for high-skilled workers is far more substitutable with remote labour. For example, the tasks of an accountant can be carried out remotely without significant loss in the quality of the service; for a machine operator, much less so.

We calibrate the model to study the impact of the containment policies. We use the classification proposed by Dingel and Neiman (2020) to determine the substitutability between onsite and remote labour for both high-skilled and low-skilled workers. And, we employ two different strategies to calibrate the containment policies implemented on the ground. In the first approach, we obtain the decline in workplace mobility from Google mobility data, and the containment rates are chosen so that the model generates the decline that we see in the data. The second strategy is to calibrate the containment rates by matching the decline in aggregate income that we obtained from the CPHS data.

Depending on the calibration strategy, we find that the containment policies implemented during the pandemic can explain between 24 and 60 percent of the increase in inequality that we see in the data. Because every lockdown policy imposes restriction on labour mobility and onsite labour is much less substitutable for low-skilled workers, these policies disproportionately impact the labour income of low-skilled workers compared to their high-skilled counterparts. This worsens the already existing income inequality between these two kinds of workers.

Looking at the disease dynamics, we find that the containment policy calibrated using Google mobility data was successful in delaying peak of the infections by 50 days compared to a scenario where no policy was implemented. Similarly, the lockdown calibrated using the alternate approach also succeeds in pushing the peak infection date by 30 days. Thus, we find that the containment policies, by restricting the labour mobility, were successful in slowing down the disease spread. Furthermore, high-skilled and low-skilled workers experience the pandemic differently. We observe that low-skilled workers suffer higher peak infection rates and a larger fraction of them get infected through the pandemic compared to high-skilled workers. Because low-skilled workers are engaged in occupations that cannot be done remotely, they choose to work more onsite compared to the high-skilled workers, resulting in higher percentage of infections and deaths among them. Thus, low-skilled workers endure a higher cost on both economic and health dimensions, with increased income inequality and higher incidence of infections.

How much transfer will be required to reduce the lockdown-induced income inequality to its pre-pandemic level? For the two different calibrations considered, the cost of such a transfer to the low-skilled workers turns out to be around 0.12 and 0.05 percent of GDP. We find that these transfers, apart from reversing the increase in inequality, also improve the effectiveness of the lockdown policies in containing the pandemic. By enabling the low-skilled workers to stay at home and not venture out for work, these transfers slow down the disease spread among the low-skilled workers and the economy as a whole. Thus, we show that in these extraordinary times, transfers contribute both as an economic as well as a health policy, and should be actively implemented along with any containment measure.

There have been several 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. (2021) 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 focuses on the substitution between onsite and remote labour in a HANK model and talks about the implications for US. Finally, there are a number of recent empirical contributions such as Montenovo et al. (2020), Mongey et al. (2021), and Dingel and Neiman (2020) that talk about the heterogeneous impacts of social distancing policies on different occupations. Our paper attempts to study the economic and health impacts of the containment policies in a developing economy, India, which is characterized by a large fraction of low-skilled workers whose ability to supply remote labour is severely limited.

The rest of the paper is organized as follows. Section 2 presents the empirical framework and estimates of inequality and infections. Section 3 describes the model and derives the equilibrium conditions. Section 4 presents the calibration strategy while the main results of the paper are discussed in section 5. Section 6 concludes.

2. Empirical Evidence

This section documents the economic and health impact of the COVID-19 pandemic and the ensuing containment policies during the first wave in India. We find that there was a massive increase in income inequality along with a sharp decline in aggregate income during this period.

2.1 Economic Impact

We use data from Consumer Pyramids Household Survey to investigate how the aggregate income and inequality changed during the period of September 2019 to December 2020.

2.1.1 Data

Consumer Pyramids Household Survey (CPHS) conducted by Centre for Monitoring Indian Economy (CMIE) is a household level panel data covering around 170,000 households. Each member of the household is interviewed once in four months and the data on income is obtained retrospectively for the previous four months. Restricting the sample to members between the age of 20 and 60 years, we have a panel of monthly income data for around 440,000 individuals across India. With the absence of any other high-frequency surveys, CPHS is the only data source that allows us to study any short-run economic phenomenon for India.[2]

Our measure of income is the real labour earnings of the workers in the past month. We deflate labour earnings using CPI and all incomes are reported in January 2020 prices.[3] The main focus of our paper is on income inequality between high-skilled and low-skilled workers, measured as the relative income between these two groups. We classify the workers who have at least some college education as high-skilled and the rest as low-skilled.

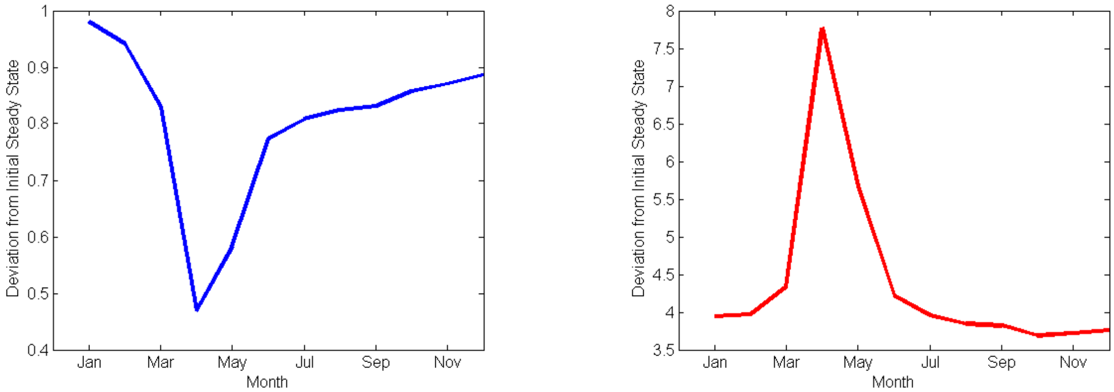
2.1.2 Empirical Specification

Even though we can directly aggregate the individual incomes using the sampling weights to obtain the aggregate income, Solon et al. (1994) points out that this could potentially lead to composition bias in the aggregate income and inequality measures. Hence, following Solon et al. (1994), Devereux (2001) and others, we exploit the panel structure of our data to run the following regression weighted by the sampling weights

$$Y_{it} = \alpha_i + T_t + \epsilon_{it}, \tag{1}$$

[2]Chodorow-Reich et al. (2020) and Karmakar and Narayanan (2020) use CPHS data to analyse the impact of demonetization on the Indian economy. More recently, Deshpande (2020) uses this data to study the effect of COVID-19 lockdown on gender gap in labour supply.

[3]We use state level monthly CPI data separately for rural and urban regions. State level data is not available from March to May 2020 and no data is available for Puducherry for June 2020. We use all-India CPI measures for these dates.



(a) Aggregate Income

(b) Inequality

Figure 1: Economic Impact

where Y_{it} is the real labour income of individual i in time t, while α_i and T_t denote the individual and time fixed effects respectively.[4] This regression captures the variation of income within a given individual over time and hence the time fixed effect T_t gives us the aggregate income after correcting for any bias introduced due to changes in composition or because of any attrition in the sample. We also run similar regressions for high-skilled and low-skilled workers separately to calculate our measure of inequality.

2.1.3 Results

Figure 1a shows the aggregate income obtained from our regression, as a deviation from the initial steady state.[5] As India went into one of the harshest lockdown on March 24 2020, we observe that the aggregate income has plummeted in April with a quick bounce back in the months of May and June, followed by a gradual but steady recovery until the end of the year. On average, the aggregate income declined by around 39% in

[4]Some of the papers analysing cyclicality of wages over a long period of time also control for labour market experience and job tenure. Unfortunately, we do not have this information in our data. But, since our analysis is over a short time span, these variables should not vary much over time and hence individual fixed effects would account for these factors.

[5]We take the average income and inequality over the period of September 2019 to February 2020 to represent the initial steady state.

the months of April to June when the lockdown was most stringent.[6]

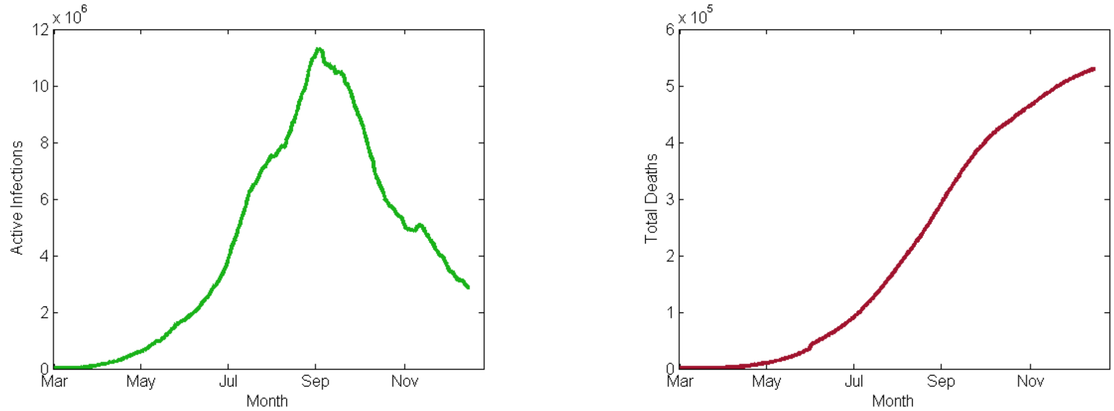
Figure 1b shows the evolution of inequality during this period. On average, a high-skilled worker earned about 3.94 times compared to a low-skilled worker before the onset of the pandemic. But once the lockdown was imposed, this inequality jumped to around 7.77 in the month of April, followed by a steady decline over the later months. On average, inequality increased by 47.4% during the months of April to June 2020.

Even though CPHS is the only nationally representative data available to study the economic impact of the pandemic, we need to take note of the recent debate around the representativeness of its sample. Drèze and Somanchi (2021b) in their recent column in Economic Times argue that the CPHS underrepresents the poor households and is biased towards richer households. They also claim that, this bias has increased over time.[7] Given that the salaried and formal sector workers were relatively less affected compared to informal sector workers, this sample bias, if present, could lead to an underestimation of the decline in aggregate income and the increase in income inequality. Drèze and Somanchi (2021a) talks about a number of household surveys conducted by different organizations during the pandemic.[8] None of these surveys are nationally representative, and they focus on specific groups of people or geographic regions. A number of these surveys point to a much sharper contraction in income and a more sluggish recovery compared to the CPHS data. For example, the second round of CSE-APU survey conducted among informal workers in 161 districts across various states in October to December 2020 shows that the average income was still 50% below pre-pandemic levels. Similarly, the third round of IDinsight survey conducted among

[6]The Stringency Index developed by Hale et al. (2020) at Blavatnik School of Government in University of Oxford shows that, India reached the maximum possible stringency of lockdown by the end of March with calibrated easing over the later months. More information on this index for India and other countries across the world can be found at https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

[7]The article can be accessed at https://economictimes.indiatimes.com/opinion/et-commentary/view-the-new-barometer-of-indias-economy-fails-to-reflect-the-deprivations-of-poor-households/articleshow/83696115.cms while the response of CMIE to this critique can be found at https://economictimes.indiatimes.com/opinion/et-commentary/view-there-are-practical-limitations-in-cmies-cphs-sampling-but-no-bias/articleshow/83788605.cms.

[8]The list of various surveys are available at https://cse.azimpremjiuniversity.edu.in/covid19-analysis-of-impact-and-relief-measures/#other_surveys.



(a) Total Active Infections (b) Total Deaths

Figure 2: Health Impact

5000 rural households across 6 states in September 2020 shows the income levels to be 74% below the pre-pandemic levels.[9] These patterns are at odds with the ones obtained from CPHS data, as it shows a stable and almost complete recovery of income by the end of 2020. Hence, in light of these findings, it is quite possible that the CPHS data does not fully capture the decline in income and the increase in inequality during the pandemic, and care should be taken in interpreting these results.

2.2 Health Impact

We measure the health impact of the COVID-19 pandemic by the number of active infections and the total deaths in the economy. The data for disease dynamics is obtained from the John Hopkins CSSE repository (Dong et al. (2020)). There has been a lot of discussion about underreporting of COVID-19 infections and deaths in India. In order to account for that, we refer to Purkayastha et al. (2021) who calculate the underreporting factor for infections and deaths using publicly available data. They find that, active infections were underreported by a factor of 11.11 while deaths were underreported by 3.56 times during the first wave of the pandemic. We correct the raw data using these

[9]More details of CSE-APU survey can be found at https://cse.azimpremjiuniversity.edu.in/cse-surveys/covid19-livelihoods-phone-survey/ while the findings of IDinsight survey can be accessed at https://www.idinsight.org/ideas-and-insights/tools/covid-19-interactive-data-dashboard/.

numbers to account for the underreporting. Figure 2a shows the total active infections in the economy while figure 2b shows the total deaths during the period of March to December 2020. Active infections peaked on September 17, 2020 when around 11 million people were infected. The pandemic had claimed around 500,000 lives by the end of 2020. We next embed a benchmark SIRD model into a macroeconomic framework to jointly explain the increase in income inequality and the progression of infections that we documented here.

3. 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 modify the model proposed by Eichenbaum et al. (2021) along two fronts. First, we extend the base model to two types of workers (high-skilled and low-skilled) supplying two types of labour (onsite and remote). Second, we model disease dynamics using a SIRD model along the lines of Fernández-Villaverde and Jones (2020) instead of a standard SIR model used in Eichenbaum et al. (2021). The containment policy is modeled as a negative productivity shock to onsite labour.

3.1 Pre-Pandemic Economy

The economy consists of a unit measure of workers out of which ψ fraction is high-skilled while $1-\psi$ of them is low-skilled. 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-skilled compared to low-skilled workers.

Before the pandemic, the high-skilled (and similarly low-skilled) 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

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

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, and the total labour supplied by worker j is given by $((1-\mu)n^j + \eta^j\hat{n}^j)$.[10] 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-skilled workers belong to occupations that can be more readily performed remotely compared to low-skilled workers, any lockdown imposed to curtail the pandemic will disproportionately affect the economic well-being of low-skilled workers compared to high-skilled workers. We estimate the elasticities η^h and η^l to find that η^l is far smaller compared to η^h in line with our 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 and hence incentivises remote labour. Finally, Γ^j denotes the transfers the workers receive from the government funded through tax χ on labour income. Initially, we set $\Gamma^j = 0$ (and hence $\chi = 0$) 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 conditions for worker j are:

[10] 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.

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

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-skilled (L^h) and low-skilled (L^l) workers to produce consumption good (Y). The firm maximizes its profit

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

where the firm combines high-skilled and low-skilled 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 difference in productivity of high-skilled and low-skilled labour while δ denotes the elasticity of substitution between them.
In equilibrium, total output must equal total consumption:

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

Labour markets for both types of workers must clear:

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

And, government budget must balance:

$$
\chi(w^h L^h + w^l L^l) = \psi\Gamma^h + (1-\psi)\Gamma^l.
$$

3.2 During Pandemic

Having developed the general equilibrium framework, we integrate it with the widely used SIRD (Susceptible, Infected, Recovered, Deceased) model proposed by Kermack and McKendrick (1927) and recently employed in economics literature by Fernández-Villaverde and Jones (2020), Bar-On et al. (2021), and others. With the advent of a pandemic, the population can be divided into five subgroups, namely Susceptible (those who have not been infected), Infectious (those who have the disease), Resolving (those who are out of the infectious state), Deceased (those who did not survive), and Recovered (those who are treated of the infection). Both high-skilled and low-skilled workers can be separated into these five groups. Let the number of high-skilled workers in these groups be $S_t^h, I_t^h, R_t^h, D_t^h$ and V_t^h while the corresponding numbers for low-skilled workers be $S_t^l, I_t^l, R_t^l, D_t^l$ and V_t^l. Let T_t^h and T_t^l be the number of newly infected people at time t respectively.

Following Eichenbaum et al. (2021), 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-skilled workers is given by $\pi_1(S_t^h C_t^{S,h})(I_t C_t^I)$ while that of low-skilled workers is given by $\pi_1(S_t^l C_t^{S,l})(I_t C_t^I)$. Terms $(S_t^h C_t^{S,h})$ and $(S_t^l C_t^{S,l})$ represent the total consumption of high-skilled and low-skilled workers who are susceptible, while $(I_t C_t^I)$ represents the total consumption of all the infected people.[11] π_1 denotes the probability of infection through the consumption channel. A susceptible person coming across an infected person can get infected irrespective of whether the infected individual is high-skilled or low-skilled. Hence, the disease spread in both high-skilled and low-skilled sectors depends on the total consumption of the infected population $(I_t C_t)$. But since the consumption patterns are different for high-skilled and low-skilled workers, the disease incidence might be different across these two groups of workers.

The second channel of transmission is through the interactions at place of work. The number of newly infected high-skilled workers through this channel is $\pi_2(S_t^h N_t^{S,h})(I_t N_t^I)$

[11]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 that of low-skilled is $\pi_2(S^l_t N^{S,l}_t)(I_t N^I_t)$. The disease transmission does not depend on the entire labour supply, but only on the time spent at the place of work. $(S^h_t N^{S,h}_t)$ and $(S^l_t N^{S,l}_t)$ represents the total hours of onsite labour supplied by susceptible high-skilled and low-skilled workers respectively. As before, the disease transmission depends on the total amount of onsite labour $(I_t N^I_t)$ supplied by all the infected workers.[12] Because the low-skilled 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-skilled and low-skilled workers through this channel are $\pi_3 S^h_t I_t$ and $\pi_3 S^l_t I_t$ respectively.

The total number of newly infected high-skilled (T^h_t) and low-skilled (T^l_t) workers are then given by

$$T^j_t = \pi_1(S^j_t C^{S,j}_t)(I_t C^I_t) + \pi_2(S^j_t N^{S,j}_t)(I_t N^I_t) + \pi_3 S^j_t I_t,$$

where $j \in \{h, l\}$. The infection rates among the high-skilled (τ^h_t) and low-skilled (τ^l_t) workers are defined as $\tau^h_t = T^h_t / S^h_t$ and $\tau^l_t = T^l_t / S^l_t$ respectively. The evolution of the susceptible population for both high-skilled and low-skilled workers is

$$S^j_{t+1} = S^j_t - T^j_t.$$

Susceptible people, after getting infected, move out of the infection pool to a resolving state with probability π_r. The evolution of the infected population is

$$I^j_{t+1} = I^j_t + T^j_t - \pi_r I^j_t.$$

People in the resolving state exit with probability π_e into either recovery or death. The resolving state evolves according to

$$R^j_{t+1} = R^j_t + \pi_r I^j_t - \pi_e R^j_t.$$

[12]Total onsite labour of all infected population is given by $(I_t N^I_t) = I^h_t N^{I,h}_t + I^l_t N^{I,l}_t$

Let π_d denote the probability of death conditional on being infected. The law of motion for the dead is given by

$$D^j_{t+1} = D^j_t + \pi_d \pi_e R^j_t,$$

while the recovered follows

$$V^j_{t+1} = V^j_t + (1 - \pi_d)\pi_e R^j_t.$$

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

$$pop^j_{t+1} = pop^j_t - \pi_d \pi_e R^j_t.$$

At the initial period, we assume ϵ fraction of total population are infected, with no recoveries or deaths. The total number of high-skilled and low-skilled 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. Detailed description of the model and the derivation of equilibrium conditions is given in appendix A.

3.2.1 Susceptible People

A susceptible worker $j \in \{h, l\}$ chooses consumption, onsite and remote labour to maximize the lifetime utility

$$U^{s,j}_t = u(c^{s,j}_t, n^{s,j}_t, \hat{n}^{s,j}_t) + \beta\Big[(1 - \tau^j_t)U^{s,j}_{t+1} + \tau^j_t U^{i,j}_{t+1}\Big],$$

subject to the budget constraint

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

τ_t^j, the infection rate of worker $j \in \{h, l\}$, is given by

$$\tau_t^j = \pi_1 c_t^{s,j}(I_t C_t^I) + \pi_2 n_t^{s,j}(I_t N_t^I) + \pi_3 I_t.$$

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.

3.2.2 Infectious People

A high-skilled or low-skilled infectious worker maximizes

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

subject to the budget constraint

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

Parameters ϕ and $\hat{\phi}$ captures the loss in onsite and remote labour productivity due to getting infected.[13]

3.2.3 Resolving People

A worker in the resolving state solves

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

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

subject to the budget constraint

$$c_t^{r,j} = (1-\chi_t)w_t^j\Big(\phi(1-\mu_t)n_t^{r,j} + \hat{\phi}\eta^j\hat{n}_t^{r,j}\Big) + \Gamma_t^j.$$

3.2.4 Recovered People

A recovered worker maximizes the lifetime utility

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

subject to the budget constraint

$$c_t^{v,j} = (1-\chi_t)w_t^j\Big((1-\mu_t)n_t^{v,j} + \eta^j\hat{n}_t^{v,j}\Big) + \Gamma_t^j.$$

3.2.5 Market Clearing

In equilibrium, the goods and labour markets clear, and the government budget balances as follows.

Labour Market:

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

Goods Market:

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

Government:

$$\chi_t(w_t^h L_t^h + w_t^l L_t^l) = (S_t^h + I_t^h + R_t^h + V_t^h)\Gamma_t^h + (S_t^l + I_t^l + R_t^l + V_t^l)\Gamma^l.$$

4. Calibration

In this section, we discuss the calibration of the parameters of the model. First, we calibrate the economic parameters and epidemiological parameters. Next, we back out the containment policies to match the underlying economic dynamics during the pandemic.

4.1 Economic parameters

Each model period represents a calendar day. We set the discount factor, β, to be equal to $0.96^{1/365}$, which corresponds to a yearly real interest rate of 4%. We set the total factor productivity, A, to be 31.93 to target the pre-pandemic (steady state) average real daily income of 138.75 Indian Rupees (INR), obtained from CPHS data. γ captures the difference in productivity of high-skilled and low-skilled workers, and has implications for the income inequality. We calibrate γ to be 0.731 to match the pre-pandemic income inequality of 3.995. For our baseline results, the elasticity of substitution between high-skilled and low-skilled labour, δ, is chosen to be 1.5 in line with the findings of Acemoglu and Autor (2011). The disutilities of onsite labour θ and remote labour $\hat{\theta}$ are calibrated to be 0.032 and 0.052 respectively to target 5 hours of onsite labour and 2 hours of remote labour for high-skilled workers in the steady-state. Following Eichenbaum et al. (2021), we set ϕ ($\hat{\phi}$), the productivity loss of onsite (remote) labour due to infections at 0.8.

Determination of ψ, η^h, η^l

We make use of the National Classification of Occupations - 2015 (NCO-2015) in order to identify high-skilled and low-skilled occupations. NCO-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.[14] 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). Table 1 shows the occupations and the associated skill levels. Consistent with our classification in the empirical analysis, we group the two highest skill levels into a high-skilled (h) category, and the rest to a low-skilled (l) category. Accordingly, occupation codes 1 – 3 in table 1 correspond to high-skilled occupations while codes 4 – 9 correspond to low-skilled occupations.

In order to find the employment share of high-skilled (ψ) and low-skilled ($1 - \psi$) occupations, we use data from Periodic Labour Force Survey (PLFS) 2018-19. It is a nationally representative survey conducted by National Sample Survey Office (NSSO) from July 2018 to June 2019, and it provides labour market information for about 420,757 individuals. Concentrating on workers from non-farm sector, the employment share of high-skilled occupations, ψ, comes out to be 26.5%.[15]

We next calculate the substitutability between onsite and remote labour for both high-skilled (η^h) and low-skilled (η^l) occupations. This is the reduction in effective labour supply when a worker substitutes one unit of onsite labour with one unit of remote labour. We make use of the classification proposed by Dingel and Neiman (2020)

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

[15] Following Bhatt et al. (2021), the non-farm sector includes National Industry Classification 2008 (NIC 2008) groups 02-99, 014, 016, and 017.

Table 1: Occupations and Skills

NCO codes	Title	Skill	Share	η
1	Legislators, Senior Officials, and Managers	IV	0.125	0.896
2	Professionals	IV	0.070	0.424
3	Technicians and Associate Professionals	III	0.070	0.458
4	Clerks	II	0.036	0.554
5	Service Workers and Sales Workers	II	0.157	0.002
6	Skilled Agricultural and Fishery Workers	II	0.035	0
7	Craft and Related Trades Workers	II	0.195	0
8	Plant and Machine Operators and Assemblers	II	0.095	0
9	Elementary Occupations	I	0.217	0

Note: The NOC codes refer to occupation divisions, the most aggregated categories. The skill levels are I: Primary Education, II: Secondary Education, III: First University Degree, IV: Post-Graduate University Degree. Share refers to the employment share of the occupation in the total workforce. η is the share of individuals in an occupation who can work remotely.
Source: Periodic Labour Force Survey 2018-19 for occupation shares, Government of India's Ministry of Labour and Employment for NCO codes and associated skills, Dingel and Neiman (2020) classification for remote work shares.

to identify the occupations that can be performed at home. They use data from O*NET to classify whether a particular occupation is feasible to be done from home or not. Combining this classification with occupational shares from PLFS, we can construct the share of WFH occupations.[16] Table 1 provides the employment and remote work shares for occupations at 1-digit level. We use the averages of these remote work shares as our measure of η.[17] Bhatt et al. (2021) uses this data to show that around 19% of the Indian workforce are employed in WFH occupations, which is similar to what we get (19.4% in our case). But, we find that there is a large heterogeneity across skill levels. Aggregating within high-skilled and low-skilled occupations, we find that the remote work shares among high-skilled (η^h) is 0.656 while that of low-skilled (η^l) is just 0.028.

[16] The occupation codes used by Dingel and Neiman (2020) classification is SOC-2010 while PLFS 2018-19 uses NCO-2004 occupation codes. We thank Vasavi Bhatt and Ajay Sharma for providing us with the crosswalk.

[17] 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.

Table 2: Economic Parameters

Parameter description		Value	Source/Target
Substitutability of remote labour			
– high-skilled	η^h	0.656	Dingel and Neiman (2020) + PLFS (2018-19)
– low-skilled	η^l	0.028	Dingel and Neiman (2020) + PLFS (2018-19)
Share of high-skilled labour	ψ	0.265	PLFS (2018-19)
Elas. of substitution between skills	δ	1.5	Acemoglu and Autor (2011)
Productivity loss due to infection	$\phi, \hat{\phi}$	0.8	Eichenbaum et al. (2021)
Discount factor	β	$(0.96)^{1/365}$	Period = day
Disutility of onsite labour	θ	0.032	High-skilled onsite labour = 5 hours
Disutility of remote labour	$\hat{\theta}$	0.052	High-skilled remote labour = 2 hours
Relative productivity	γ	0.731	Steady-state inequality = 3.995
Total factor productivity	A	31.93	Steady-state income = 138.75 INR

Thus, onsite labour is much more substitutable among high-skilled compared to low-skilled workers, and this has important implications for income inequality as the pandemic and the containment policies curtail the movement of labour. Table 2 shows the values of all the calibrated economic parameters.

4.2 Epidemiological parameters and Containment policies

Choice of π_r,π_e,π_d

Consistent with the epidemiological literature such as Maier and Brockmann (2020) and Prem et al. (2020), we assume that once people get infected, they stay infectious for 7 days on average, beyond which they move into the resolving state. Since the model frequency is daily, we set the probability of entering the resolving state, π_r, to be 1/7. Once in the resolving state, we assume that an average patient takes 10 days to exit this state and either recover or die. Thus, we choose the probability of exiting the resolving state, π_e, to be 0.1, similar to Fernández-Villaverde and Jones (2020) and Bar-On et al. (2021). On average, a case lasts for 17 days in total. Purkayastha et al. (2021), after taking into account under-reporting of deaths, estimate the infection fatality rate (IFR) for India to be 0.46%.[18] We use this value for π_d.

Initial Conditions and $\mathcal{R}_0$

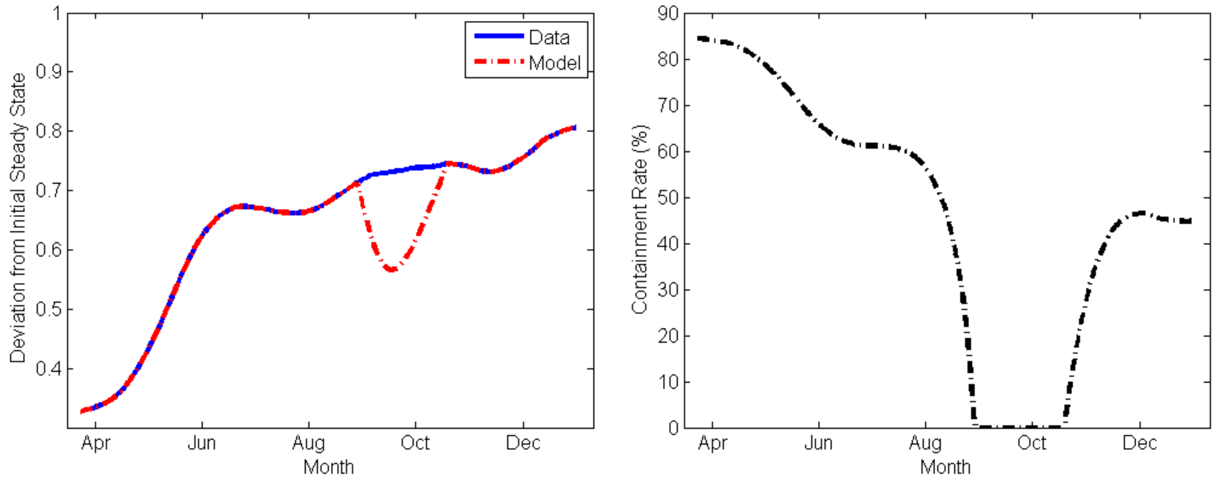
We normalize the total pre-pandemic population to be one, and we set ϵ, the fraction of people initially infected to be 10^{-6}. With a population of 1.38 billion, this translates to 1380 infections at the start date. Using data on infections from John Hopkins CSSE repository corrected for under-reporting, we find that India crossed 1380 active infections on March 17, 2020 (there were 1388 active infections on this date). So, we consider March 17, 2020 to be the start date of the pandemic in our model.

We next choose the value of the basic reproduction number, $\mathcal{R}_0$. It represents the expected number of individuals who will be infected by a single infected individual over the course of the disease when everyone is susceptible. We follow Eichenbaum et al. (2021) in choosing $\mathcal{R}_0$ to match the disease dynamics. In particular, we set $\mathcal{R}_0$ such that the peak date of the infections in the model match that of the data. As we saw in section 2, the total active infections peaked on September 17, 2020 which corresponds to 185 days from the model start date. Importantly, the number of days it takes for the infections to peak depends crucially on the containment policies implemented on the ground. Hence, we need to take a stand on the lockdown policies that were in place during that time, which is what we turn to next.

Containment Policies

In the model, the lockdown policy implemented by the government is captured by the containment rates μ_t. We use two different calibration strategies to back out the daily containment rates, μ_t, over the period of March 24 to December 31, 2020. In the first approach, we make use of Google Mobility data, and the containment rates are chosen so that the model generates the decline in workplace mobility that we observe in the data. The second strategy is to calibrate the containment rates to match the decline in aggregate income that we estimated from the CPHS data. We use both these ap-

[18] Purkayastha et al. (2021) finds that, by using only reported deaths, the estimate of IFR during the first wave is 0.13%. After correcting for under-reporting, this estimate jumps to 0.46%.



(a) Labour Mobility

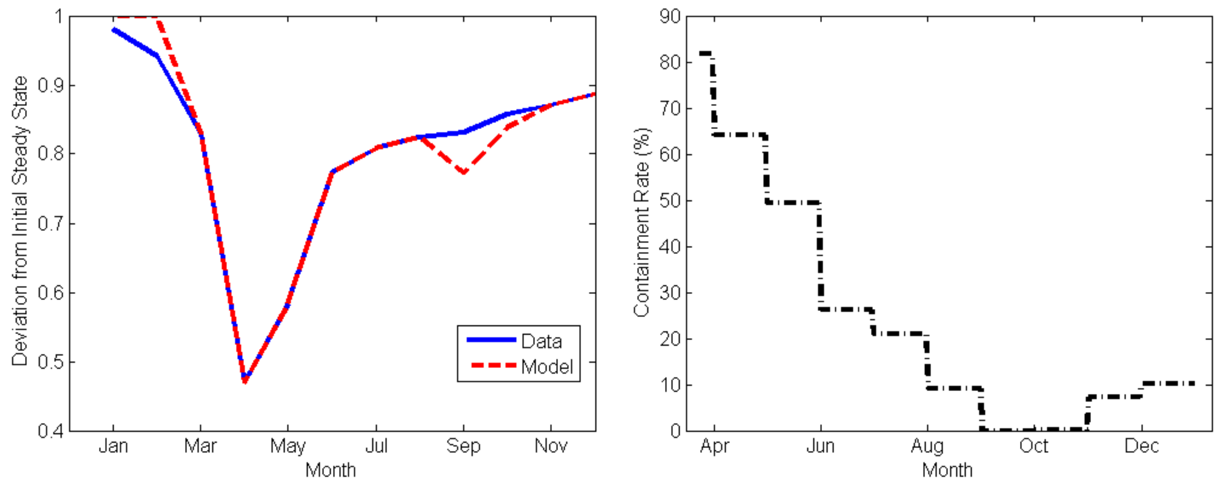
(b) Containment Rate

Note: Data series refers to workplace mobility data from Google Mobility Reports while the model series refers to model generated onsite labour of high-skilled workers.

Figure 3: Lockdown Calibration using Google Mobility Data

proaches for calibration as each data source has its own advantages and disadvantages as we discuss below.

Google Mobility Reports, using anonymous location data, document the change in time spent by people across various location categories. Some of the places that Google releases mobility data include retail and recreation, groceries, parks, transit stations, workplaces, and residences. We match the decline in onsite labour from the model with the decline in workplace mobility in this data to calibrate the containment rates. In particular, we assume that Google mobility data predominantly reflects the mobility patterns of high-skilled labour. We believe that this is a valid assumption to make for two reasons. One, smartphones, even though more prevalent than before, are still a luxury product. Accordingly, most of the smartphone users (about whom Google collects mobility data) tend to be high-skilled workers. Two, workers need to have a fixed location of work for Google to recognize it as a workplace. This is more characteristic of a salaried high-skilled worker compared to a daily wage-earner. So, we map the labour



(a) Aggregate Income

(b) Containment Rate

Note: Data series refers to aggregate income from CPHS while the model series refers to aggregate income generated by the model.

Figure 4: Lockdown Calibration using CPHS Income Data

mobility patterns in the data with onsite labour of high-skilled workers in the model.[19]

Figure 3a shows the Google workplace mobility data and the model generated decline in high-skilled onsite labour. As can be seen, once the lockdown was imposed in late March, the mobility declines by more than 70% followed by a gradual increase till the end of the year. The model does a good job of capturing this change in onsite labour except during the months of September and October when the infections peaked. As the infections start peaking, high-skilled workers in the model reduce their onsite labour significantly and shift towards remote labour. Even when the calibrated containment rate is set at zero for those periods, the model generated decline in high-skilled onsite labour is much larger than the decline observed in the mobility data. Figure 3b shows the implied containment rates that we obtain from this calibration ex-

[19]Another option is to interpret the mobility data as representing the aggregate onsite labour. As we will see in the next section, the aggregate onsite labour in our model doesn't decline as much as the Google mobility data even when the containment rates are set to the maximum. This is because, the low-skilled workers do not reduce their onsite labour by much in response to the containment policies as they have very low substitutability towards remote work.

ercise. Except during the peak infection days, the model is able to exactly match the patterns in the Google mobility data.[20]

An alternative approach for calibrating the containment rates is to match the decline in aggregate income obtained from CPHS data with the model counterpart. Since CPHS reports data at a monthly frequency, we assume that the containment rate remains constant within a given month. Figure 4a shows the decline in aggregate income from CPHS data and the model counterpart. The aggregate income decreased by around 55% once the lockdown was implemented with a steady recovery in the later months. Just as in the case of mobility data, the model does a good job of capturing the decline in income except during the peak infection months of September and October. As the infection peaks, both high-skilled and low-skilled workers cut down their supply of onsite labour and this causes further decline in income. This model generated decline in income is larger than what we observe in CPHS data even when we set the containment rates to be zero during these times. Figure 4b shows the containment rates generated by matching the income data.

The main advantage of using Google mobility to calibrate is that we have daily data on changes in labour mobility which helps us in calibrating the containment rates at a daily frequency. The limitation is, even though the data might be extensive, we do not have any information on how representative the underlying sample is. On the other hand, CPHS is a nationally representative data with a large sample. But it has monthly data and hence, we can calibrate our containment rate only at the monthly frequency. Additionally, the recent concerns of CPHS data under-representing the poor (low-skilled) workers could potentially bias the estimated decline in aggregate income and hence our calibrated containment rates. So, we make use of both the calibration strategies.

Reproduction number $\mathcal{R}_0$: Having calibrated the containment rates, we can now choose the value of $\mathcal{R}_0$ so that the model generated infections peak at 185 days just as in the data. This gives us a $\mathcal{R}_0$ value of 1.739 under the first calibration strategy and a value of

[20]One way to improve the calibration around the peak infection days is to assume negative containment rates. But negative containment policy translates to actively encouraging onsite labour in place of remote work, and it is safe to assume such a policy was never implemented on the ground.

Table 3: Epidemiological Parameters

Parameter description		Value	Source/Target
Probability of exiting infection	π_r	1/7	Infectious period = 7 days
Probability of case resolution	π_e	0.1	Resolution period = 10 days
Probability of death	π_d	0.0046	Purkayastha et al. (2021)
Initial fraction of infected population	ϵ	10^{-6}	1380 individuals
Google Mobility Data			
Reproduction number	$\mathcal{R}_0$	1.739	Peak infection date
Probability of infection (consumption)	π_1	1.03×10^{-6}	Time Use Survey (2019)
Probability of infection (labour)	π_2	0.004	Time Use Survey (2019)
Probability of infection (social interaction)	π_3	0.109	Time Use Survey (2019)
CPHS Income Data			
Reproduction number	$\mathcal{R}_0$	1.626	Peak infection date
Probability of infection (consumption)	π_1	9.65×10^{-7}	Time Use Survey (2019)
Probability of infection (labour)	π_2	0.0038	Time Use Survey (2019)
Probability of infection (social interaction)	π_3	0.1022	Time Use Survey (2019)

1.626 under the second strategy.

Choice of π_1, π_2, π_3

In a standard SIR model, susceptible people get infected when they come in contact with infected people. The number of new infections in the population through such "social" interactions can be written as

$$T_t = \xi S_t I_t,$$

where ξ is the transmission rate of the infections. ξ measures the expected number of individuals who can get infected in time t by someone who is already infected. Observe that out of these ξ individuals, only a fraction of S_t 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 ξS_t. Multiplying this by total number of infected individuals I_t, we get the total number of new infections.

To obtain the value of ξ, one can use the following relation:

$$\mathcal{R}_0 = \xi/\pi_r,$$

where $\mathcal{R}_0$ is the basic reproduction number and $1/\pi_r$ is the average number of days a person stays infectious (7 days in our calibration). Since we have already calibrated $\mathcal{R}_0$ to match the infection dynamics, we can immediately back out the value of the transmission probability ξ.

In this paper, we assume that the transmission probabilities due to consumption, work and social interactions add up to ξ. At the beginning of a pandemic, we then have

$$\pi_1 \times C^2 + \pi_2 \times N^2 + \pi_3 = \xi,$$

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 on average spend on these different activities. Time Use Survey data for India (2019) suggests that an average Indian spends 10 hours per day outside their home. Out of these, around 4.8 hours are spent on work, 0.8 hours are spent on consumption-related market activities and the rest on activities that could lead to social interactions. Details of the time use data and time allocation across various activities are provided in appendix B. It follows that

$$\frac{\pi_1 \times C^2}{\pi_1 \times C^2 + \pi_2 \times N^2 + \pi_3} = \frac{0.8}{10},$$

and

$$\frac{\pi_2 \times N^2}{\pi_1 \times C^2 + \pi_2 \times N^2 + \pi_3} = \frac{4.8}{10}.$$

Solving these equations, we find $\pi_1 = 1.03 \times 10^{-6}$, $\pi_2 = 0.004$, and $\pi_3 = 0.109$ when we calibrate using Google mobility data. Calibration using CPHS income data gives $\pi_1 = 9.65 \times 10^{-7}$, $\pi_2 = 0.0038$, and $\pi_3 = 0.1022$. Thus, even though we use two different data sources for calibration, the transmission probabilities are quite similar under both the cases. Table 3 shows the epidemiological parameters calibrated using both these strategies.

5. Results

In this section, we analyse the economic and health impacts of the containment policies calibrated from the data by comparing them to a counterfactual "no policy" scenario. We measure economic impact using aggregate output and income inequality between high-skilled and low-skilled workers. The inequality is captured using relative consumption (or income) of high-skilled to low-skilled workers (c_t^h/c_t^l).[21] We use peak infection rate and also the number of days it takes for the infections to peak as the measure of health effects. Peak infection rates capture the maximum stress that the healthcare services might come under while the days to peak measures the speed at which the infection transmits through the economy. Finally, we introduce economic transfers designed to keep inequality unchanged and discuss about its impact on economic and health outcomes.

5.1 Containment Policies

As we saw in the previous section, we calibrate lockdown policies using two different strategies. We refer to the containment rates and transmission probabilities obtained from Google mobility data as "Lockdown 1" while the ones calibrated using CPHS income data as "Lockdown 2".

[21] Inequality is calculated as the weighted average of relative consumption across the different cohorts i.e. susceptible, infectious, resolving, and recovered.

$$\text{Inequality}_t = \frac{S_t^l(c_t^{s,h}/c_t^{s,l}) + I_t^l(c_t^{i,h}/c_t^{i,l}) + R_t^l(c_t^{r,h}/c_t^{r,l}) + V_t^l(c_t^{v,h}/c_t^{v,l})}{S_t^l + I_t^l + R_t^l + V_t^l}.$$

Table 4: Comparison with Data

	Data	Lockdown 1	Lockdown 2
Economic Impact			
Δ Income (%)	33.66	48.75	33.59
Δ Inequality (%)	37.71	22.32	9.10
Health Impact			
Days to Peak	185	185	185
Days to Double	13.65	11.63	11.79

Note: Data refers to CPHS. Lockdown 1 is calibrated using Google mobility while Lockdown 2 is calibrated using CPHS income data. Change in income and inequality refer to the percentage change over the months of March to June compared to the respective pre-pandemic levels. Days to peak measures the number of days it takes for the total infections to peak, with March 17 taken to be day 1. Days to double measures the average number of days for the total infections to double from the start till the day infections peaked.

5.1.1 Economic Impact

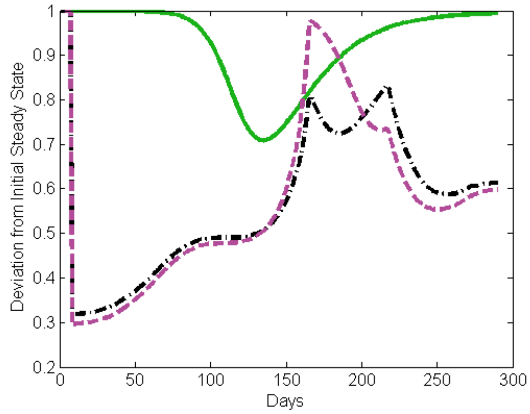
We measure the economic impact of the containment policies using the change in income and inequality over the months of March to June 2020 when the lockdown was most stringent. Table 4 compares the model generated changes with the data counterparts. As we saw in section 2, aggregate income in CPHS data declined by about 34%, while inequality jumped by around 38% over these months. Comparing these numbers with the results of lockdown 1, the model calibrated to match the decline in labour mobility predicts a much sharper income decline of 49%. Thus, the lockdown calibrated using this strategy is much more intense than what is implied by the CPHS data. We will discuss the implications of this finding later.

We next look at inequality between high-skilled and low-skilled workers, the main focus of our paper. Under lockdown 1, the inequality jumps by 22% on average compared to 38% observed in the data. Thus, our model calibrated to match the decline in labour mobility can explain around 60% of the increase in inequality seen during the months of March to June 2020. Lockdown 2 calibrated using CPHS data generates an income decline of 34% observed in the data by design. Under this calibration, the inequality between the two groups of workers increases by 9% over the same time period. Thus, the lockdown strategy calibrated to CPHS income data can generate about 24% of the increase in inequality observed in the data.

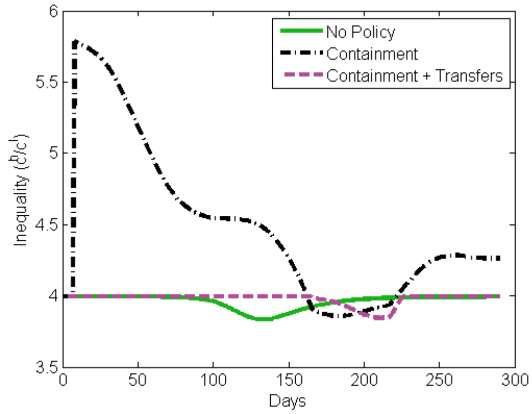
Depending on the calibration strategy, our model can explain between 24% and 60% of the observed increase in inequality during the months of March to June, 2020. As the containment measures restrict labour mobility, it imposes a massive cost on onsite labour for both high-skilled and low-skilled workers. But since onsite labour is significantly less substitutable in low-skilled compared to high-skilled occupations, the lockdown worsens the already existing inequality between these two groups of workers.

In order to understand the impact of the calibrated containment policies, we simulate a counterfactual scenario where no lockdown policies are implemented. Figures 5 and 7 show the dynamics of aggregate income and inequality under various policy scenarios for both the calibrations. Panel A of table 5 reports the simulated economic and health indicators during the months of March to June under lockdown 1 while panel B reports the same for lockdown 2. In the scenario where no lockdown policies are in place, model predicts a marginal decline in income during these months compared to a sharp contraction when the containment is in place. Similarly, the inequality hardly changes in the no policy scenario in contrast to an increase between 24% and 60% when the lockdown policies are implemented.

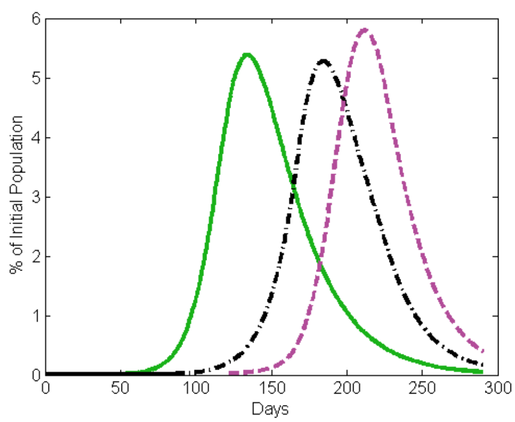
Figures 6 and 8 show the dynamics of onsite and remote labour for both high-skilled and low-skilled workers under both the calibrations. Even in the no policy scenario, both groups of workers internalize the risk of infections and substitute towards remote work. Containment policies once implemented are successful in further reducing the onsite labour of high-skilled workers and shift towards remote labour. Low-skilled workers on the other hand do not respond much to these containment policies. They



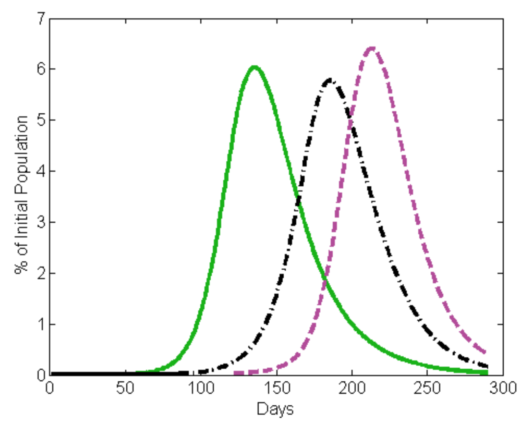
(a) Aggregate Output



(b) Inequality



(c) High-Skilled Infections

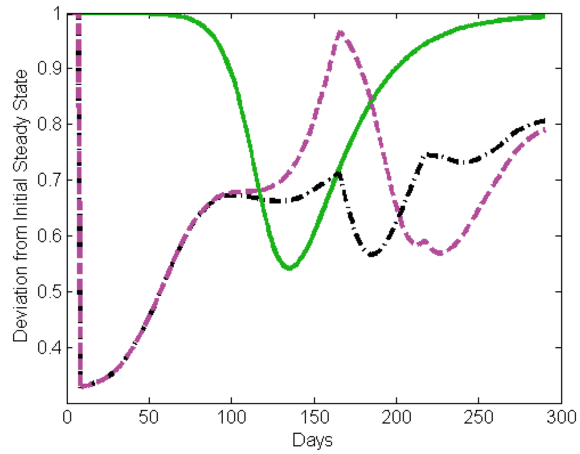


(d) Low-Skilled Infections

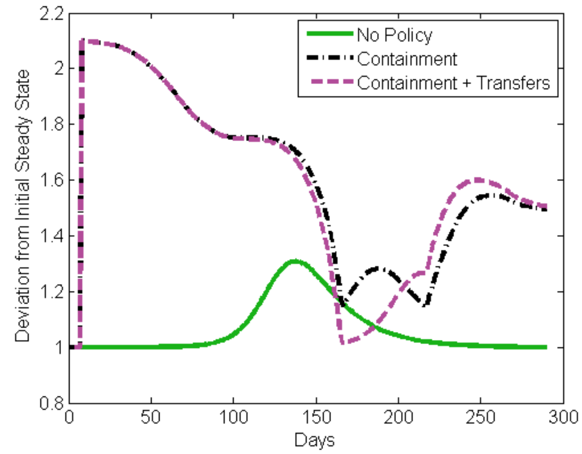
Figure 5: Lockdown 1: Economic and Health Outcomes

continue to mostly work onsite as remote labour is not very productive for these workers.

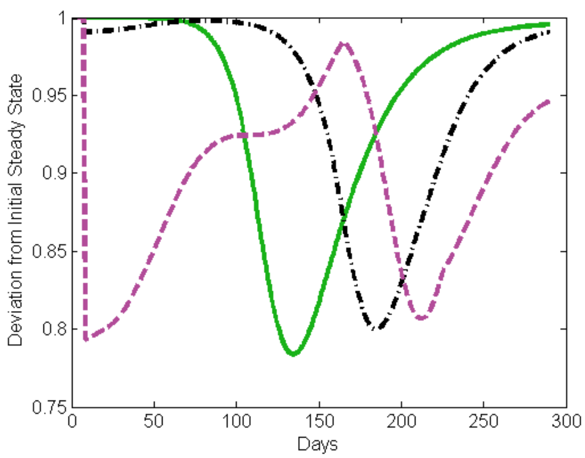
Thus, lockdown policies implemented to contain the spread of the pandemic has led to a large decline in income and a massive increase in inequality between high-skilled and low-skilled workers. We next analyse how successful these policies were in



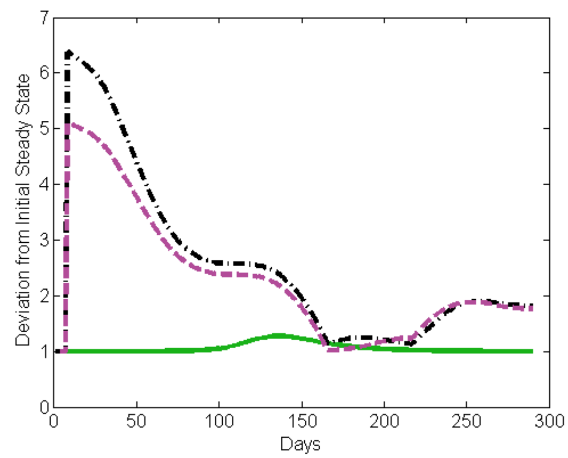
(a) High-Skilled Onsite Labour



(b) High-Skilled Remote Labour



(c) Low-skilled Onsite Labour



(d) Low-Skilled Remote Labour

Figure 6: Lockdown 1: Labour Dynamics

slowing down the spread of infections.

5.1.2 Health Impact

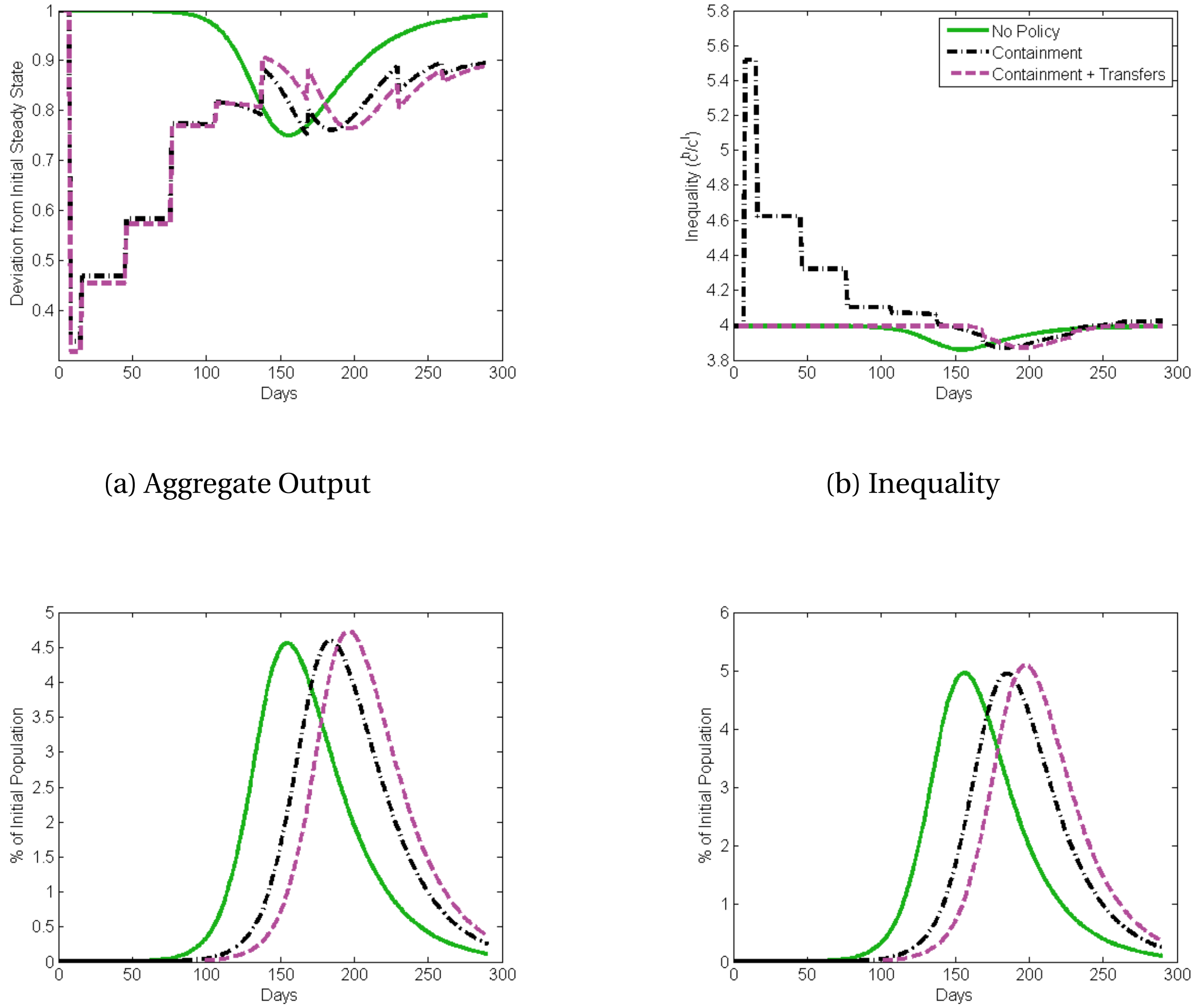
The model is calibrated to match the peak infection date of 185 days that we find in the data. Table 4 also shows the number of days it takes for the infections to double from the start till the peak date. Model generates doubling days of around 11.7 days under both the calibrations, and this is comparable to 13.7 days that we see in the data. Even though we do a good job of capturing the days to peak and doubling days of the infections, the model generates much higher peak infections compared to the data. The data shows around 1% of the entire population were infected at the peak date. But the model generates a peak infection rate of around 5% across both the calibrations.

Now we compare the disease dynamics under lockdown with that of the no policy scenario to evaluate the effectiveness of these lockdown policies. As can be seen from figures 5 and 7, containment policies were successful in slowing down the pandemic. The results in table 5 shows that, the containment policy calibrated using labour mobility data (lockdown 1) was successful in pushing the peak infection date by 50 days. The simulation shows that the infections would have peaked in 135 days instead of 185 days observed in the data if no containment policies were implemented. Calibration from CPHS data suggests that, lockdown was successful in delaying the peak by 30 days, with peak date in no policy scenario occurring in 155 days. Thus, irrespective of the calibration strategy, containment policies implemented on the ground were successful in slowing down the disease transmission.

Even though the implemented policies were successful in delaying the onset of the peak, they did not reduce the peak infection rates by much. This is because, the containment rates are calibrated to be zero when the infections reach the peak and hence it is equivalent to having no lockdown during those peak days. Thus, the lockdown did not flatten the peak of infections, but it managed to slow down the pandemic spread in India.[22]

Finally, we observe that high-skilled and low-skilled workers experience the pan-

[22] India started its phased relaxation of lockdown from June while the infections peaked in September. Our finding is consistent with some of the discussions in popular press like https://www.news18.com/news/india/lockdown-may-not-have-flattened-covid-19-curve-but-it-bought-india-time-as-it-approaches-infection-peak-261236 html



(a) Aggregate Output

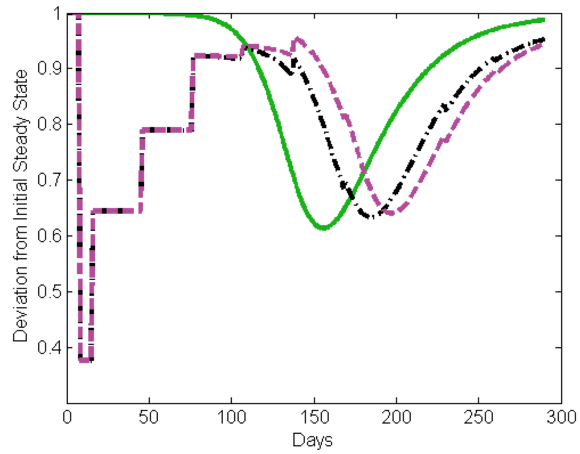
(b) Inequality

(c) High-Skilled Infections

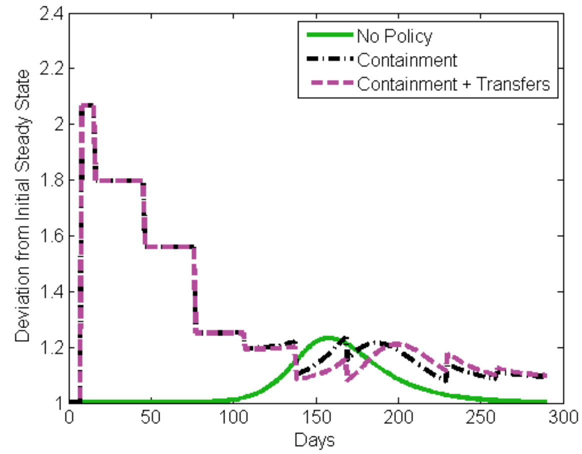
(d) Low-Skilled Infections

Figure 7: Lockdown 2: Economic and Health Outcomes

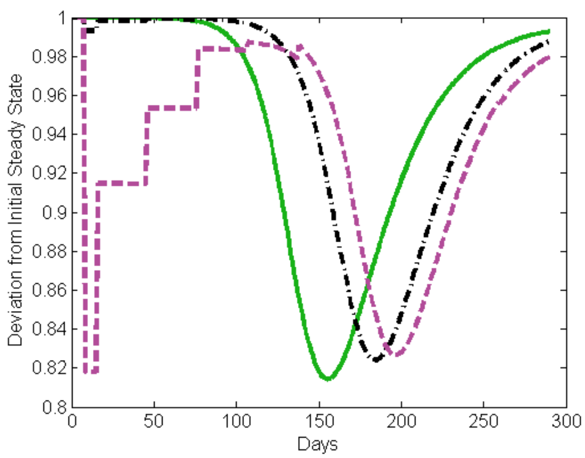
demic differently. Table 5 shows that low-skilled workers suffer higher peak infection rates compared to high-skilled workers. And, a higher fraction of low-skilled workers end up contracting the infections compared to high-skilled workers. For instance, under lockdown 1, around 55.7% of low-skilled workers would be infected by the end of the pandemic compared to 51.3% of high-skilled workers, and this pattern holds true



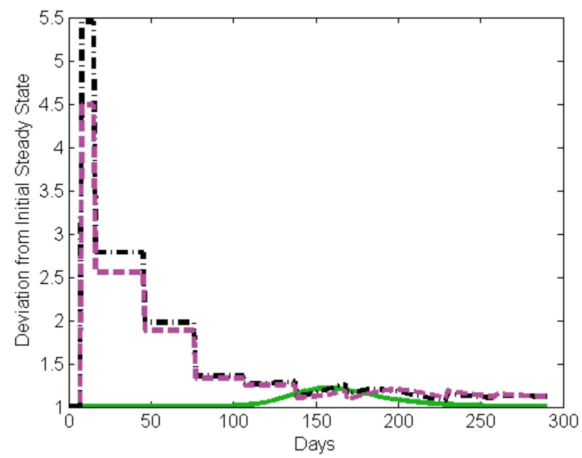
(a) High-Skilled Onsite Labour



(b) High-Skilled Remote Labour



(c) Low-Skilled Onsite Labour



(d) Low-Skilled Remote Labour

Figure 8: Lockdown 2: Labour Dynamics

across all the policy scenarios. This is because, as seen from figures 6 and 8, low-skilled workers optimally choose to work more onsite compared to high-skilled workers as they have low substitutability between onsite and remote labour. Thus, low-skilled workers inspite of the risk of infections venture out more for work as they have no other choice, and hence end up contracting more infections compared to high-skilled workers.

While analysing the effects of containment policies, two clear observations emerge. First, there exists a trade-off between containing the infections and its effect on economic activity. No policy scenario where no containment policies are in place imposes the least cost on the economy. Lockdown 1 calibrated from Google mobility data was effective in delaying the peak by 50 days, but it was also the costliest with an income decline of around 50%. Lockdown 2 obtained from CPHS data is relatively cheaper to implement with an income loss of 34%, but it was less effective as it managed to push the peak by only 30 days.

Second, the low-skilled workers are disproportionately affected on both economic and health outcomes compared to high-skilled workers. As the containment measures impose a massive cost on onsite labour, both high-skilled and low-skilled workers substitute towards remote work. Since remote labour is not very productive for low-skilled workers, the lockdown worsens the already existing inequality with an increase in the range of 24% to 60% when the containment policies are implemented. And, since onsite labour is significantly less substitutable for low-skilled workers, they optimally choose to work more onsite compared to high-skilled workers. This causes the containment policies to be less effective for low-skilled workers leading to a higher incidence of infections among them. In our setup, low-skilled workers face an excessive burden on both economic and health fronts, with increased inequality and higher incidence of infections compared to high-skilled workers.

5.1.3 Implications for CPHS Data

As we already discussed in section 2, there are some concerns that CPHS data underrepresents the poor households and this could potentially underestimate the decline in aggregate income. Since we use Google data to calibrate, we can use our model to examine the extent of this bias, if any. Figure 9 compares the decline in income obtained from CPHS data with the model generated decline in income implied by our calibra-

Table 5: Containment Policies

Policy	Loss of Output (%)	Δ Inequality (%)	Transfers (% GDP)	Days to Peak		Peak Infection (%)	
				High-Skill	Low-Skill	High-Skill	Low-Skill
Panel A: Lockdown Strategy 1							
No Policy	1.17	-0.15	-	134	136	5.38	6.03
Lockdown	48.75	22.32	-	184	186	5.28	5.78
Lockdown + Transfers	50.20	0	0.12	212	213	5.80	6.40
Panel B: Lockdown Strategy 2							
No Policy	0.338	-0.04	-	155	156	4.56	4.96
Lockdown	33.59	9.10	-	184	185	4.60	4.95
Lockdown + Transfers	34.46	0	0.05	196	197	4.73	5.09

Note: Loss of output refers to the total decline in aggregate output as a percentage of initial steady state from March to June when the containment policies were implemented. Change in inequality measures the average change in relative consumption compared to the pre-pandemic inequality of 3.995 over the same period. Total transfers are measured as a percentage of GDP. Days to peak measures the number of days it takes for the infections to peak from the start of the pandemic. Peak infection reports the maximum infection as a percentage of initial population for both high-skilled and low-skilled workers.

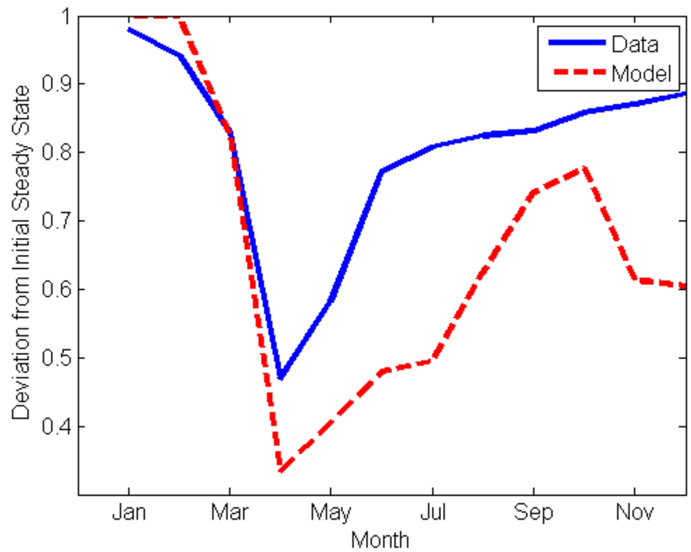
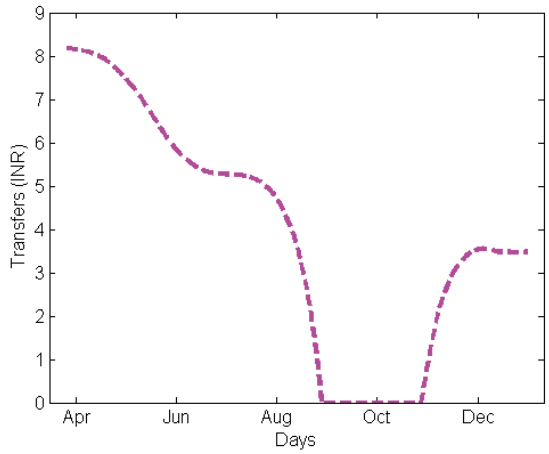


Figure 9: Income Decline: CPHS data versus the model

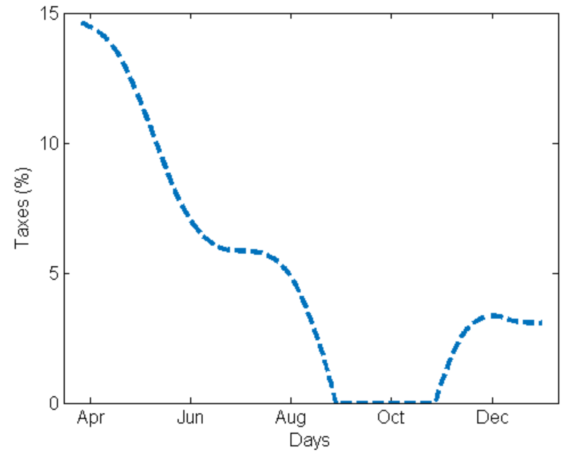
tion. Our model calibrated to match the decline in labour mobility generates a much deeper recession followed by a more sluggish recovery compared to the CPHS data. This is consistent with a number of survey evidences that document a much much sharper contraction followed by a more gradual expansion post COVID-19 lockdown. This exercise gives us an indication of how much CPHS underestimates the decline in aggregate income.

5.2 Containment with Transfers

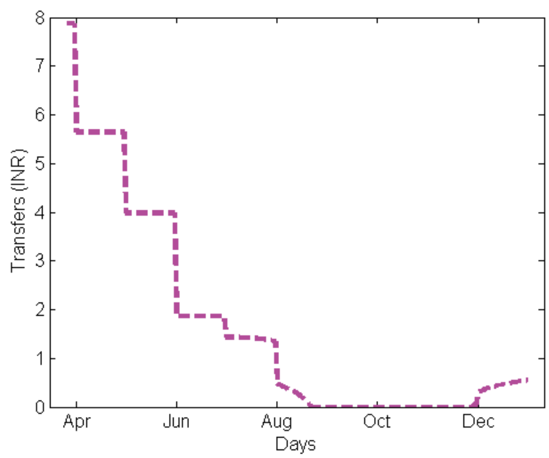
Even though the containment policies were successful in controlling the spread of infections, it also exacerbated the already existing inequality between high-skilled and low-skilled workers. We now perform a policy experiment of implementing direct transfers for low-skilled workers along with the containment policies, to remedy the additional inequality generated by the lockdown. These transfers targeted towards low-skilled workers (Γ_t^l) are chosen to bring the inequality back to pre-pandemic levels, while high-skilled workers do not receive any transfers ($\Gamma_t^h = 0\,\forall t$). Figure 10 shows the path of the transfers each low-skilled worker receives under both the calibrations and



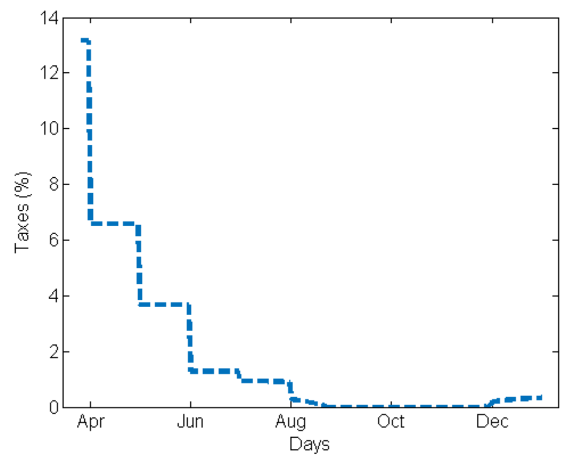
(a) Lockdown 1: Transfers



(b) Lockdown 1: Tax Rates



(c) Lockdown 2: Transfers



(d) Lockdown 2: Tax Rates

Figure 10: Transfer Policies

the associated taxes the government levies on all the workers to fund these transfers. As can be seen from figures 5b and 7b, the implementation of cash transfers successfully reverses the increase in inequality under both the containment scenarios.

Table 5 shows the magnitude of transfers (as a percentage of GDP) required to remove the excess inequality under the two calibrations. We obtain the total expenditure of this policy by aggregating the transfers received by each low-skilled worker over the entire non-agricultural low-skilled workforce of 209 million workers obtained from World Bank data.[23] To put it in perspective, we represent this as a share of India's GDP, which is around 200 trillion Indian Rupees (approximately 2.65 trillion USD).

As can be seen from table 5, lockdown 1 calibrated using mobility data generates a large increase in inequality and hence require more transfers amounting to 0.12% of GDP. Lockdown 2 on the other hand is less stringent and hence needs direct transfers of around 0.05% of GDP to take care of the excess inequality introduced by this policy. These transfers should be considered as the bare minimum policy intervention needed to preserve the status-quo on inequality. Any containment policy affecting onsite labour without the accompanying transfers will compound the problem of inequality.

Apart from reversing the excess inequality, targeted transfers also improve the effectiveness of containment policies in controlling the pandemic. As can be seen from table 5, with transfers in place, both the lockdown measures succeed in delaying the infection peak date even further compared to a pure containment scenario. As shown in figures 6 and 8, the transfers received by low-skilled workers enable them to reduce their onsite labour and spend more time at their homes. In the case of lockdown 1, low-skilled onsite labour goes down by just 3.8% when there are no transfers. But in the presence of transfers, the low-skilled workers are able to reduce their onsite labour by 7.8%. This helps in containing the disease spread among the workforce. Introducing transfers increase the number of days for the infections to peak from 185 days in a pure containment scenario to 213 days and hence reduce the speed of disease transmission. Importantly, transfers directed towards low-skilled workers slows down the infections among high-skilled workers as well by delaying their peak infection dates. Just like in

[23] Total labour force: https://data.worldbank.org/indicator/SL.TLF.TOTL.IN?locations=IN. Employment in agriculture: https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS?locations=IN. According to this data, the total labour force in India in 2019 is 495 million, out of which the non-agricultural workforce is 284 million. Low-skilled workers constitutes 73.5% of the non-agricultural labour, which amounts to 209 million.

the case of pure containment case, even though transfers delay the onset of the peak, it doesn't reduce the peak infection rates as the transfers are calibrated to be zero during these peak days. This pattern of targeted transfers delaying the peak infections for both high-skilled and low-skilled workers holds for the alternate calibration as well.

Even when the low-skilled 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 54% of the people would eventually be infected due to this disease, compared to 54.5% under lockdown 1 and 55.7% 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-skilled workers choose to supply more onsite labour compared to the pure containment scenario. When lockdown 1 is implemented with transfers, the reduction in high-skilled onsite labour is around 25.4% compared to a 26.5% fall when there are no transfers, thus leading to increased production. These two effects compensate for the reduction in low-skilled labour and mitigate any further loss in output.

These results show that direct 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 worsens the already existing inequality. Transfer policies designed to take care of the excess inequality, apart from balancing the economic costs faced by high-skilled and low-skilled workers, also improves the effectiveness of the containment measures.

6. Conclusion

Following the imposition of a lockdown triggered by COVID-19, income inequality in India jumped up. In order to jointly explain this increase in inequality and the disease dynamics, we integrate a standard epidemiological model within a general equilibrium framework with high-skilled and low-skilled workers. Calibrating our model containment policies to those implemented on the ground, we show that these lockdown policies impose disproportionate economic costs on low-skilled workers, and can explain between 25 to 60 percent of the observed increase in income inequality. On top of that, because low-skilled workers do not have the luxury to work from home, the incidence of infections is also higher compared to high-skilled workers. Finally, introducing transfers for low-skill workers designed to remove the excess inequality improves the performance of containment policies by further delaying the peak date of the infections.

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Appendix

A. Model Solution

A.1 Susceptible People

High-skilled (and similarly low-skilled) susceptible workers choose their consumption, onsite and remote labour to maximize their lifetime utility

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

subject to the budget constraint

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

τ_t^j, the infection rate of worker $j \in \{h, l\}$, is given by

$$\tau_t^j = \pi_1 c_t^{s,j}(I_t C_t^I) + \pi_2 n_t^{s,j}(I_t N_t^I) + \pi_3 I_t.$$

Assuming the flow utility function as $u(c_t^{s,j}, n_t^{s,j}, \hat{n}_t^{s,j}) = log(c_t^{s,j}) - \frac{\theta}{2}(n_t^{s,j})^2 - \frac{\hat{\theta}}{2}(\hat{n}_t^{s,j})^2$, the first order conditions are:

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

where $\lambda_t^{sb,j}$ and $\lambda_t^{\tau,j}$ denotes the Lagrange multipliers of budget constraint and infection rate for worker j respectively.

A.2 Infectious People

A high-skilled or low-skilled infectious worker maximizes

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

subject to the budget constraint

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

Assuming the same utility function as before, the first order conditions are

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

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

A.3 Resolving People

A high-skilled or low-skilled worker in resolving state maximizes

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

subject to the budget constraint

$$c_t^{r,j} = (1-\chi_t)w_t^j\Big(\phi(1-\mu_t)n_t^{r,j} + \eta^j\hat{\phi}\hat{n}_t^{r,j}\Big) + \Gamma_t^j.$$

Assuming the same utility function as before, the first order conditions are

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

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

A.4 Recovered People

A recovered worker maximizes the lifetime utility

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

subject to the budget constraint

$$
c_t^{v,j} = (1-\chi_t) w_t^j \Big((1-\mu_t) n_t^{v,j} + \eta^j \hat{n}_t^{v,j} \Big) + \Gamma_t^j.
$$

The first order conditions are given by

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

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

B. Calibration of Transmission Probabilities

Our estimates of the transmission probabilities are based on The Time Use in India (2019) report prepared by the Ministry of Statistics and Programme Implementation, Government of India. This report classifies activities as per the International Classification of Activities for Time Use Statistics 2016 (ICATUS 2016). Activities are classified at the 1-digit (major division), 2-digit (division) and 3-digit (group) levels. To compute the fraction of time spent on consumption and work (outdoor) on a typical day, we look at the all-India data for urban male in the 15-59 years age group (Statement 8, page 31). First, we compute the time spent by an average respondent outside his home (the implicit assumption being that the likelihood of getting infected is negligible inside the home). We get this number by adding the time spent on Employment and related activities (major division 1), Unpaid volunteer, trainee and other unpaid work (major division 5), Socializing and communication, community participation and religious practice (major division 7), Culture, leisure, mass-media and sports practices (major division 8). The amount of time spent on these activities per day is around 10 hours. The number of hours spent working is roughly 5 hours. To compute the time spent on consumption, we assume that the roughly 2.4 hours per day on Culture, leisure, mass-media and sports practices are spread uniformly over nine activities (Unfortunately, the report does not provide the fraction of time spent on each of these finer activities). Out of these, we assume that three activities are primarily performed outside the home: Attending/visiting cultural, entertainment and sports events/venues (division 81), Sports participation and exercise and related activities (division 83), Travelling time related to culture, leisure, mass-media and sports practices (division 86). Accordingly, an individual spends about 0.8 hours on consumption-related activities outside the home.