SAFER WORKING SPACES AT CORONAVIRUS TIME: A NOVEL USE OF ANTIBODY TESTS

(PRELIMINARY AND INCOMPLETE)

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Abstract

As SARS-Cov 2 spreads worldwide, governments struggle to keep people safe without collapsing the economy. Social distancing and quarantines have proven to be effective measures to save lives, yet their impact on the economy is becoming apparent. The major challenge faced by many countries at this point of the pandemic, is to find a way to keep their critical industries such as health, telecommunications, national security, transportation, food and energy functioning while having a safe environment for their workers. In this paper we propose a novel approach based on periodic SARS-CoV 2 antibody testing to reduce the risk of contagious within the working space, and evaluate it using stochastic simulations of the health evolution of the workforce. Our simulations indicate that the proper use of testing and quarantine of workers suspected of being infected can greatly reduce the number of infections while improving the productivity of the company in the long run.

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1 INTRODUCTION

As SARS-Cov 2 spreads worldwide, governments struggle to keep people safe without collapsing the economy. Social distancing and quarantines have proven to be effective measures to save lives, yet their impact on the economy is becoming apparent. The major challenge faced by many countries at this point of the pandemic, is to find a way to keep their critical industries such as health, telecommunications, national security, transportation, food and energy functioning while having a safe environment for their workers. In this paper we propose a novel approach based on periodic SARS-CoV 2 antibody testing to reduce the risk of contagious within the working space, and evaluate it using stochastic simulations of the health evolution of the workforce.

Our approach assumes firms use antibody tests to screen workers because this is the best available option. The gold standard for diagnosis of SARS-CoV 2 is the RT-PCR, which is expensive, requires laboratories and is scarce in most countries. There also exist antigen test that require a nasopharyngeal swab, just like PCR. These tests exist in point-of-care modality, where they have shown poor results, and also in-laboratory modality, with better outcomes. Yet the latter cannot be applied at the workplace, which makes them unattractive for most firms. If there existed a good antigen rapid test that could be applied at point-of-care we would use it, but none has succeeded so far. The antibody rapid test we consider requires a simple finger prick blood sample to obtain a result in 10-15 minutes. These tests can be taken at the workplace and have high specificity (95%) and an acceptable sensitivity (93%) after 7 days of symptoms onset [15]. Antibody tests detect the presence of specific anti SARS-CoV 2 antibodies, which reflect concurrent or previous viral infection. There are some that already have FDA and/or its equivalent European (CE) fast-track approval.

We propose to apply these tests to the asymptomatic working population assuming antibody responses similar to those described for symptomatic patients, as some authors have seen that serum antibody levels do not correlate with clinical severity [17]. By applying this model we intend to detect as early as possible an asymptomatic worker that could be shedding the virus without knowing. Detecting and isolating him/her will prevent future spreading of the virus from this patient. Furthermore, doing so let us identify his/her close contacts and put them into quarantine as well, preventing, ideally, further spreading the disease.

As mentioned above, the test we use is not a diagnostic test, so a person that comes up positive should be confirmed with PCR, if PCR were not available we recommend considering the person as COVID-19 positive. There has been an increasing concern regarding sanitary measures when a worker has been identified positive for the virus that could lead to closing a factory. We believe that a responsible management strategy applying safety measures, like the one we propose and study in this paper, would justify that the sanitary authority react less harshly when positive cases are detected.

Finally we would like to emphasize that this is a tool to be added to other recommendations to avoid the virus spreading at work, such as social distancing, personal protective elements, home-
office, shifts, no casino lunches and sanitation among others.

2 MATHEMATICAL MODEL

In this section we describe what is known about the disease in terms of incubation, symptom, and shedding periods, which is crucial for the disease evolution. We also focus on the contagiousness of the virus and the production of antibodies that can be detected to isolate a potentially contagious patient. Then, we describe the relevant parameters and random variables and the protocols that are considered for the evaluation of the use of antibody tests and shifts to reduce the risk of contagious within an organization. Finally, we describe the Montecarlo simulation model and compare it with the well known SIR and SEIR epidemiological models.

2.1 Evolution of the disease: description and assumptions

Our data on the time line of viral behavior for asymptomatic patients is extrapolated from what the literature describes as mild cases, given that there is insufficient data for asymptomatic patients and some authors have demonstrated similar characteristics between both types of individuals. [23].

Because it is not known when the person becomes infected, it is assumed that a patient becomes contagious two days before showing symptoms [2], [7]. We also assume that the time until the symptoms show up, given that the sick person will show up with symptoms, is distributed according to a lognormal distribution [10]. The data suggests that mild cases experience a duration of symptoms of 7-14 days [2].

The viral shedding period, i.e., the period when the infected person is contagious, starts approximately 2 days before the onset of symptoms [2], [7] and ends between 10 to 14 days after symptoms subside [2]. The study in [23] finds that an infected person has a higher viral load within the first 5 days since symptoms onset, and hypothesizes that this could lead to a higher contagious rate. However, there is no high quality evidence so far that confirms this hypothesis. Therefore, we assume a homogeneous contagious rate over time [20], [21].

Additionally, we assume that asymptomatic infected individuals do not get complications from the infection, and therefore do not die as a consequence of the virus. That is, they recover spontaneously and we do not know who has done it.

Currently, the quarantine in place in Chile works as follows: if a person shows symptoms and the infection is confirmed by a PCR test, she is quarantined immediately until symptoms subside, and for an additional period of 14 days [12], [14]. We also consider that an asymptomatic person without a previous history of COVID-19 with a positive antibody test – either for IgM or IgG - is potentially

\[2\] IgM e IgG are immunoglobulins that form part of our immune response against different microorganism. They are two of the various known antibodies that humans produce. IgM is usually associated to the acute phase of an infection, whilst IgG can be seen during the acute phase and posterior to it, lasting longer in our system. It may prevent future reinfection or prepare for a better immune response in case of reinfection. Antibody rapid tests are specific for the detection of anti-SARS-CoV 2 antibodies.
an infectious agent, and therefore is quarantined for 14 days. If during this period, he/she presents symptoms, the quarantine is extended for another 14 days from the time the symptoms subside. If mild symptoms develop, they last randomly in a range from 5 to 10 days [2]. In both cases, the person at the end of the quarantine is considered recovered, and thus, not contagious.

The WHO-China Joint Mission Report, [2] found that 81% of the infected population presents mild symptoms, while other authors have found that this percentage is 61% for mild cases [13]. An article from the Imperial College COVID-19 Response Team, [6] estimated that only 2/3 of the infected present recognizable symptoms. Additionally, another study on pregnant women showed that 80% might carry the virus without symptoms [16]. In a long-term care facility in the United States, 56% of those who tested positive with PCR were asymptomatic [9]. Thus, combining current available information, we assume that 50% of the infected population will develop the disease in a oligoasymptomatic fashion. We chose not to consider higher incidence as found for specific-population studies (e.g., pregnant or long-term care facility) or suggested by recent antibody testing on random populations, as this might lead to over estimation. Identifying these groups is key for pandemic control because asymptomatic patients and patients with very mild COVID-19 symptoms may not seek health care, nor receive diagnosis, which leads to underestimation of the burden of COVID-19. We note that the oligoasymptomatic might shed the virus just as symptomatic patients [23], [5].

The model’s aim is to ensure a safe work environment, we therefore develop an algorithm for the interpretation of the test results that misses the least active viral shedding workers despite the possibility of quarantining a non-shedding worker until he gets his PCR done. Given the low prevalence of confirmed SARS-CoV 2 to date in Chile, and that the first reported case was less than two months ago, we decided to interpret the antibody results for asymptomatic-under screening population as follows:

Notice that the interpretation of the antibodies’ results that is explained above for the oligoasymptomatics under screening population differs from the interpretation done in cases of known COVID-19 patients who afterwards get tested with antibodies. We remark that the latter are not the subject of this study. Regarding those who came in contact with the virus and after some time get tested with antibodies and show IgM (-) and IgG (+), to date there is insufficient evidence to confirm their immunity, nonetheless there are some studies that suggest that reinfection is unlikely [1], [4]. Thus, in the near future, when more knowledge is acquired, the data gathered from screening will provide valuable information for public health policy.
| IgM | IgG | Interpretation | Viral shedding asm. |
|-----|-----|----------------|-------------------|
| −   | −   | Still has not come in contact with virus or is in antibody window period. | No* |
| +   | −   | Acute phase of infection | Yes |
| +   | +   | Acute phase of infection | Yes |
| −   | +   | Acute phase of infection** | Yes |

*We know that a negative antibody test does not rule out viral shedding, but the only way to confirm that would be by PCR testing (or a good antigen test) and that is not currently available. Therefore, we interpret this result as the equivalent of having citizens going to work without screening, assuming they are not spreading the virus.

** We decided to interpret this result as active infection to increase our sensitivity despite losing specificity, but ensuring a safer return to work. This is under the consideration that: 1) we are testing asymptomatic patient that have no previous history of COVID-19, ii) many will have previous antibody tests to compare (because we are testing twice a week), iii) the probability of having contact with a COVID-19 positive person is still low in Chile (at least for non-health worker), iv) negative IgM could be a false negative (this range between 5-15%), and v) It would take approximately one month for a person infected by SARS-CoV2 to seroconvert from antibody negative to IgM (+) / IgG (+), and then to IgM (-) / IgG (+), and given that the first COVID-19 case in Chile was less than 2 month ago, we considered this unlikely.

2.2 Parameters

- $R_0 = \text{Basic reproduction number (expected number of cases directly generated by one case in a population where all individuals are susceptible to infection). This number is estimated at the beginning of the pandemic and is a function of } R_0 = \tau c E(I_p) \text{ where } \tau \text{ is the transmissibility (i.e., probability of infection given contact between a susceptible and infected individual), } c \text{ is the average rate of contact between susceptible and infected individuals, and } E(I_p) \text{ is the duration of infectiousness} \ [8]. \text{ Several estimates have been reported in the literature} \ [18], \ [22].$

- $R_0(w) = \text{Basic reproduction number within the organization or company. With strict measures, this number can be reduced considerably.}$

- $\Pr(\text{IgM}^+ \text{ or IgG}^+ | \text{Infected}) = \text{sensitivity of combined antibody test. It varies as follows: from 1 to 7 days since symptoms onset equal to 11%, between days [8,14] equal to 92.9% and 96.8% after 14 days} \ [15].$

- $\Pr(\text{IgM}^- \text{ and IgG}^- | \text{Susceptible}) = \text{specificity of the test.}$

- $p_s = \Pr(\text{sint}) = \text{Probability of becoming symptomatic, given that the person got the virus.}$

- $\Pr(S) = \text{probability of being susceptible (not infected yet) at the beginning of the planning horizon.}$

- $\Pr(E) = \text{probability of being exposed and not contagious at the beginning of the planning horizon.}$
• Pr(I) = probability of being sick and contagious at the beginning of the planning horizon.

• Pr(R) = probability of being sick and recovered at the beginning of the planning horizon. Note that Pr(S) + Pr(E) + Pr(I) + Pr(R) = 1.

• $S_h$ = number of hours in a shift.

2.3 Random variables

• $o_s$ = time until symptoms show up, given that the person will be symptomatic.

• $I_p$ = Viral shedding period.

• $d_s$ = Duration of symptoms.

• $N_S(t) = \text{number of workers that are susceptible at day } t.$

• $N_E(t) = \text{number of workers that are exposed at day } t.$

• $N_I(t) = \text{number of workers that are infected and contagious at day } t.$

• $N_R(t) = \text{number of workers that have recovered from the virus at day } t.$

• $W_S(t) = \text{number of workers that are susceptible and working at day } t.$

• $W_E(t) = \text{number of workers that are exposed and working at day } t.$

• $W_I(t) = \text{number of workers that are infected, contagious, and working at day } t.$

• $W_R(t) = \text{number of recovered workers, working at day } t.$

• $W(t) = W_S(t) + W_E(t) + W_I(t) + W_R(t) = \text{Total number of workers working at day } t.$

• $N_{pop}(t) = \text{number of total people in the total population of interest.}$

• $N_{popS}(t) = \text{number of susceptible people in the total population of interest.}$

• $N_{popI}(t) = \text{number of infected people in the total population of interest.}$

Therefore, we estimate the daily probability of getting infected at day $t$ ($p_c(t)$) as follows:

$$p_c(t) = \frac{R_0(u)}{E(I_p)} W_I(t) W(t) (S_h/16) + \frac{R_0}{E(I_p)} N_{popI}(t) N_{pop}(t) ((16 - S_h)/16)$$
2.4 Protocols

Our analysis compares the following protocols:

1. **Protocol 0 (No Protocol)**: This is the baseline protocol, where only workers that show up symptoms are quarantined. They return to work 14 days after symptoms subside.

2. **Protocol 0(shut down)**: This protocol is similar to Protocol 0, except that in the case of a symptomatic worker, the company is closed for 14 days. All workers return to work after the quarantine, except for those who show symptoms, who stay 14 extra days, after symptoms subside. This protocol has been used in some companies in Chile by the Regional Health Authority (Seremi de Salud). As a result, many companies are currently operating with great uncertainty.

3. **Protocol ABT\(k\)**: This protocol includes antibody tests every \(k\) days for all its workers. If the test is positive for either \(IgM\) or \(IgG\), the worker is quarantined for 14 days unless he shows symptoms at some point. In the latter case he stays 14 extra days, after symptoms subside.

4. **Protocol Shift\(_{14}\)**: This protocol considers two shifts of 14 days each. If a worker is infected and symptomatic, then the regular quarantine applies for him.

5. **Protocol Shift\(_{14}\) + ABT\(k\)**: This protocol is the combination of shifts of 14 days and the use of antibody tests for workers that are in an active shift.

2.5 Algorithm for Simulations of Protocols

The flowchart diagrams below in Figures 1 and 2 describe the logic of the simulations developed to evaluate the protocols designed to reduce the risk of infection and closure of plants when going back to work. First, we introduce some additional notation. Let \(N\) be the total number of individuals at the beginning of the simulation (i.e., working population size) and \(T\) the planning horizon under study. To ease notation, we will assume that all random variables described in the previous section can be grouped in one joint distribution \(\mathcal{D}\) – although most of them are independent. To be more precise, the random variables we are considering are the following:

- Proportion of initial population at each compartment.
- Days until symptom onset and duration of symptoms.
- Duration of infection after symptoms vanish.
- Transition probability from susceptible to exposed given number of infected workers.
- Antibody presence in serological test.
For each individual $i = 1, \ldots, N$, denote by $c^j_i \in \{S, E, I, R\}$ his health state at time $t$, $\hat{c}^j_i \in \{S, E, I, R\}$ his observed state at time $t$ (for example, the decision maker might believe the worker is susceptible although in reality he is incubating the disease), and $a^j_i \in \{W, Q\}$ the working state at time $t$ (work or quarantine). For Protocol Shift$_{14}$, we classify workers at home for 14 days as quarantined.

We encode a protocol by two functions $\varphi$ and $\psi$. The first one, $\psi$, decides the observed state of an individual based on any indication of illness the protocol is allowed to measure – e.g. symptoms for Protocols 0, serological test and symptoms for the rest. Note that given the stochastic nature of this indicators, the function $\psi$ takes as argument the vector of previous observed states, the current activity of each individual, and a random state drawn from $\mathcal{D}$ given the actual health state and activities. The second function, $\varphi$, decides whether the individual is allowed to work or must go into quarantine. It takes as input the vector of observed states and the activities.

In each iteration, nature draws from $\mathcal{D}$ the new health state of the population given the history of health states up to that point, and the activity of each worker. The distribution of workers in quarantine or work is relevant since it determines which workers can get infected by whom. Then, the protocol takes as input the current activities and the history of observed states, along with hyper-parameters such as duration of quarantine and frequency of serological testing if applies, and uses the decision rules described above to updates the activity of each individual.

After $T$ iterations the algorithm stops and outputs the full history of states and activities for every individual. Specifically, let $S^j_i = (c^j_i, \hat{c}^j_i, a^j_i)$ be the vector describing a worker $i$, then $\mathcal{S}_t = (S^j_i | i = 1, \ldots, N)$ and the algorithm outputs ($\mathcal{S}_t | 0 \leq t \leq T$).
Generate Initial Population:
- Initial population state is drawn from initial distribution:
  \( \hat{X}_0 = \{x_i | 1, \ldots, N \} \sim \mathcal{D} \).
- All individuals are assumed to start at work:
  \( A_0 = \{x_i = \text{work} | i = 1, \ldots, N \} \).
- All individuals are assumed to be ‘susceptible’
  \( \hat{X}_0 = \{x_i = \text{susceptible} | i = 1, \ldots, N \} \).

Protocol:
- Quarantine Length
- Initial quarantine
- Serological test frequency

Environment updates states according to previous states, activities and transition distribution:
\( \hat{X}_t = \mathcal{D}(\hat{X}, \cdot, t \leq 1), A_t \)

Output:
- History of state
  \( \{X_t | 0 \leq t \leq T \} \)

Figure 1: Flowchart of the algorithm.

2.6 Relationship between Simulations and SIR and SEIR Models

In this subsection, we study the relationship between our modeling of the disease spreading in a contained population compared to the results obtained from the well known SIR and SEIR models. In what follows, we briefly describe these models and find the equivalency between the parameters described above and those used in the SIR/SEIR models.

SIR model is described by the following three differential equations [19]:

\[
\begin{align*}
\frac{dS}{dt} &= -\frac{\beta IS}{N}, \\
\frac{dI}{dt} &= \frac{\beta IS}{N} - \gamma I, \\
\frac{dR}{dt} &= \gamma I,
\end{align*}
\]

where \( S \) is the stock of the susceptible population, \( I \) the stock of infected individuals, \( R \) the stock
of recovered population and $N$ the entire population. [The model assumes the fraction of the population that dies is small and therefore can be ignored.] Additionally, $R_0 = \frac{\beta}{\gamma}$ and $\frac{1}{\gamma}$ is the average time until recovery. Therefore, we can solve the SIR model using the parameters of our model by calculating $\gamma = \frac{1}{E(C_p)}$ and $\beta = R_0 \frac{1}{E(C_p)}$.

Studies show however that the incubation period of the disease can be significant \[3\], \[10\], \[11\]. To account for this, we consider the extended version of the previous model known as SEIR, where an extra compartment of exposed (E) individuals is added between susceptible and infectious states. Exposed individuals are already infected with the disease, but have not yet started to infect the susceptible population. Assuming the incubation period is a exponential random variable\[3\] with mean $\alpha^{-1}$, the set of differential equations that model the evolution of the disease can be stated as

\[3\] In our simulation, this is not the case, as the incubation period is a lognormal random variable of mean $E(t_s) = 2$. 

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**Figure 2: Flowchart of the Protocol.**
follows:

\[
\begin{align*}
\frac{dS}{dt} &= -\frac{\beta IS}{N}, \\
\frac{dE}{dt} &= \frac{\beta IS}{N} - \alpha E, \\
\frac{dI}{dt} &= \alpha E - \gamma I, \\
\frac{dR}{dt} &= \gamma I.
\end{align*}
\]

Under the assumptions we stated, the incubation period lasts until 2 days before symptoms start to develop. Thus, we have \( \alpha = \frac{1}{E(t_s) - 2} \). Using this combination of parameters \( \alpha, \beta \) and \( \gamma \), we can find the trajectories in the SEIR model. The graphical solution is displayed in Figure 3 along with the solution obtained using our scheme.

Note that the SIR and SEIR models do not factor any type of measure to control the disease. In the simulations displayed in the results section, the evolution of the disease was affected by actions that helped prevent or diminish the spread. The plots in Figure 3 show the mean trajectory of the number of susceptible, exposed, infected and recover individuals according to our model if no measure was taken.

3 Data

In what follows we describe the data used in Section 4

4 Results

In this section we describe the evolution of the disease obtained through simulations with different protocols. To summarize the discussion, we measure the performance of each protocol using metrics that are relevant to the objective of having safe working spaces. In general, we are interested in the health conditions of the workers, and the monetary costs of implementing a protocol (e.g., cost and number of total of serological tests). See section 6 of Appendix of Figures.

The main results can be summarized as follows:

- \( ABT \) diminishes the number of infected individuals by \( x\% \) with respect to the baseline, without significantly impact the number of active workers.

- Shift and Shift + \( ABT \) are the safest ones, but the number of active workers is reduced to half.

- Evidently, \( ABT_1 \) is the safest among \( ABT \), but it also diminishes the number of workers the most, and is the most expensive to implement.

\footnote{We ignore vital dynamics to simplify the model and because they do not play a significant role in the applications we are considering.}
| Parameter | Value |
|-----------|-------|
| $R_0$     | 1.6   |
| $R_0(w)$  | 3     |
| $S$       | $1 - 7d = 11\%, 8 - 14d = 93\%, \geq 15d = 97\%(*)$ |
| $E$       | 0.97  |
| $p_s$     | 0.5   |
| $\Pr(S)$  | 0.983 |
| $\Pr(I)$  | 0.017 |
| $\Pr(R)$  | 0.00  |
| $S_h$ (hrs) | 8    |
| $0_s$ (days) | $\ln N(\mu = 5.1, \sigma^2 = 1.8)$ (**) |
| $d_s$     | $U[7,10]$ (***) |
| $I_p$     | $2 + d_s + U[5,10]$ |

(*) See reference [15].

(**) See references [3], [10], and [11].

(***) [2] reports a median time from onset to clinical recovery for mild cases of approximately 2 weeks. Thus, we adjusted this time to 7-10 days because we consider oligoasymptomatic patients.

- Shut down diminishes the number of active workers substantially, but it’s the less effective protocol in terms of infection propagation.

### 4.1 Sensitivity Analysis

We examine how sensitive are our recommendations to changes in two of the parameters we consider. Namely, we will simulate the $ABT_3$ protocol under different values for the sensitivity of the test, and the duration of the post-symptom infection. We vary the former between 0 and 1, whereas the latter takes the value of a uniform random value whose mean and length of interval are changed.

Table of results in the appendix.

### 5 Applications

Currently we are in the process of applying some combinations of the protocols described above with specific firms and government agencies. We will report these cases when they are implemented and results can be observed.

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6 Appendix of Figures

6.1 SEIR Model

Figure 3: Comparison between our agent based simulation and the solution of the SEIR aggregate system. We used $\alpha = 1/3$, $\gamma = 1/22.5$, $R_0 = 2$, $I(0) = 0.01$ and $\beta = \gamma R_0$. 
Figure 4: Evolution of SEIR model with $\alpha = 1/3$, $\gamma = 1/22.5$, $R_0 = 2$, $I(0) = 0.01$ and $\beta = \gamma R_0$.

Figure 5: Simulation of evolution of infection using our simulation approach with $\alpha = 1/3$, $\gamma = 1/22.5$, $R_0 = 2$, $I(0) = 0.01$ and $\beta = \gamma R_0$.

6.2 Results
Figure 6: Cumulative distribution of number of infected workers at work on different times (2, 3, 4 and 5 months). $R_0 = 1.6$, $R_0(w) = 3$ and initial prevalence = 0.75%.

6.3 Sensitivity Analysis
### Table 1: Mean and Standard Deviation of percentage of infected workers at work as a fraction of total workers at work for different protocols. $R_0 = 1.6, R_0(w) = 3$ and initial prevalence = 0.75%.

| Protocol   | stat | 60   | 90   | 120  | 150  |
|------------|------|------|------|------|------|
| ABT₃       | Mean | 0.29%| 0.29%| 0.27%| 0.26%|
|            | SD   | 6.98e-03 | 6.81e-03 | 6.85e-03 | 6.38e-03 |
| No Protocol| Mean | 1.50%| 1.62%| 1.55%| 1.40%|
|            | SD   | 2.37e-02 | 2.47e-02 | 2.3e-02  | 2.17e-02 |
| Shift₁₄    | Mean | 0.46%| 0.45%| 0.45%| 0.46%|
|            | SD   | 1.13e-02 | 1.14e-02 | 1.17e-02 | 1.25e-02 |
| Shut Down  | Mean | 0.36%| 0.35%| 0.35%| 0.34%|
|            | SD   | 8.5e-03  | 8.28e-03 | 8.42e-03 | 8.29e-03 |

### Table 2: Mean and Standard Deviation of cumulative number of infections as a percentage of the total population for different protocols. 100 Workers. $R_0 = 1.6, R_0(w) = 3$ and initial prevalence = 0.75%.

| Protocol   | stat   | 60   | 90   | 120  | 150  |
|------------|--------|------|------|------|------|
| ABT₃       | Mean   | 3.68%| 4.92%| 6.10%| 7.25%|
|            | SD     | 3.68 | 4.35 | 4.84 | 5.27 |
| No Protocol| Mean   | 6.92%| 10.78%| 14.52%| 17.87%|
|            | SD     | 7.98 | 11.43 | 13.89 | 15.39 |
| Shift₁₄    | Mean   | 3.21%| 4.34%| 5.44%| 6.51%|
|            | SD     | 3.05 | 3.69 | 4.19 | 4.60 |
| Shut Down  | Mean   | 3.67%| 4.97%| 6.26%| 7.53%|
|            | SD     | 3.15 | 3.79 | 4.32 | 4.74 |

### Table 3: Total infected, and mean number of workers per day. 100 Workers. $R_0 = 1.6, R_0(w) = 3$ and initial prevalence = 0.75%.

| Protocol   | Total_Infected | Working |
|------------|----------------|---------|
| Shift₁₄    | 6.7%           | 50%     |
| ABT₃       | 7.4%           | 99%     |
| Shut Down  | 7.8%           | 77%     |
| No Protocol| 18.5%          | 99%     |
Figure 7: Probability density function of total number of infected workers at different times (2, 3, 4 and 5 months). $R_0 = 1.6$, $R_0(w) = 3$ and initial prevalence = 0.75%.

| Iterations | ABT 3 | No Protocol | Shift 14 | Shut Down |
|------------|-------|-------------|----------|----------|
| 1000       | 4.24% | 3.74%       | 4.66%    | 5.28%    |
| 2000       | 3.06% | 2.65%       | 3.23%    | 3.62%    |
| 3000       | 2.50% | 2.17%       | 2.63%    | 2.96%    |
| 4000       | 2.20% | 1.88%       | 2.29%    | 2.53%    |
| 5000       | 1.99% | 1.68%       | 2.05%    | 2.26%    |
| 6000       | 1.81% | 1.53%       | 1.87%    | 2.08%    |
| 7000       | 1.68% | 1.42%       | 1.73%    | 1.92%    |
| 8000       | 1.57% | 1.33%       | 1.62%    | 1.80%    |
| 9000       | 1.48% | 1.25%       | 1.52%    | 1.70%    |
| 10000      | 1.40% | 1.19%       | 1.44%    | 1.61%    |

Table 4: Coefficient of Variation of the mean number of infected workers as the number of iterations increases. 100 Workers. $R_0 = 1.6$, $R_0(w) = 3$ and initial prevalence = 0.75%.
Figure 8: Percentage of infected workers across time. $R_0 = 1.6$, $R_0(w) = 3$ and initial prevalence = 0.75%.

| Sensitivity | Total Infected | Infected Working Days | Fraction of Days without Infected Workers | Mean Workers |
|-------------|----------------|-----------------------|------------------------------------------|--------------|
| 0.00        | 10.13          | 88.16                 | 0.67                                      | 97.70        |
| 0.20        | 9.33           | 74.50                 | 0.70                                      | 98.20        |
| 0.40        | 8.59           | 63.20                 | 0.73                                      | 98.79        |
| 0.60        | 7.85           | 53.96                 | 0.76                                      | 98.54        |
| 0.80        | 7.66           | 50.49                 | 0.77                                      | 98.54        |
| 0.95        | 7.26           | 46.41                 | 0.78                                      | 98.21        |
| 0.97        | 7.25           | **46.15**             | **0.78**                                  | **98.29**    |
| 1.00        | 7.26           | 46.12                 | 0.78                                      | 98.54        |

Table 5: Summary of results for protocol ABT$_3$ with different values of test sensitivity. In bold the default scenario. 100 Workers, 156 days. $R_0 = 1.6$, $R_0(w) = 3$ and initial prevalence = 0.75%.
Figure 9: Infected working days. $R_0 = 1.6$, $R_0(w) = 3$ and initial prevalence = 0.75%.
Figure 10: Fraction of days with at least one worker infected at work. $R_0 = 1.6$, $R_0(w) = 3$ and initial prevalence = 0.75%.
Figure 11: Mean number of days since infection to quarantine. $R_0 = 1.6$, $R_0(w) = 3$ and initial prevalence = 0.75%.
| Post-symptom Infectious Period | Protocol | Total Infected Workers | Infected Man–Days | Percentage of Days without Infected Workers | Daily Avg. Number of Workers |
|-------------------------------|----------|------------------------|-------------------|---------------------------------------------|-----------------------------|
| U[0,1]                        | ABT₃     | 6.49                   | 36.43             | 82                                          | 98.46                       |
| No Protocol                   |          | 9.66                   | 80.13             | 69                                          | 99.31                       |
| U[1,3]                        | ABT₃     | 6.93                   | 40.41             | 81                                          | 98.52                       |
| No Protocol                   |          | 11.37                  | 103.99            | 64                                          | 98.75                       |
| U[3,5]                        | ABT₃     | 7.01                   | 42.19             | 80                                          | 98.01                       |
| No Protocol                   |          | 13.65                  | 138.17            | 57                                          | 98.34                       |
| U[3,7]                        | ABT₃     | 7.20                   | 44.17             | 79                                          | 98.09                       |
| No Protocol                   |          | 14.51                  | 153.75            | 55                                          | 98.01                       |
| U[5,7]                        | ABT₃     | 7.28                   | 45.54             | 79                                          | 98.08                       |
| No Protocol                   |          | 15.88                  | 175.75            | 53                                          | 98.45                       |
| U[5,10]                       | ABT₃     | 7.25                   | 46.15             | 78                                          | 98.29                       |
| No Protocol                   | 18.57    | 218.57                 | 47                | 99.12                                       |                             |
| U[7,10]                       | ABT₃     | 7.41                   | 47.88             | 77                                          | 99.22                       |
| No Protocol                   | 20.25    | 247.99                 | 43                | 99.59                                       |                             |
| U[7,14]                       | ABT₃     | 7.80                   | 53.20             | 75                                          | 97.57                       |
| No Protocol                   | 24.18    | 321.07                 | 34                | 98.43                                       |                             |

Table 6: Summary of results for protocol ABT₃ and No Protocol with different values of post-symptom infection time. In bold the default scenario. 100 Workers, 156 days. \( R_0 = 1.6, R_0(w) = 3 \) and initial prevalence = 0.75%.