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Firm behavior during an epidemic

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Abstract

We derive a model in which firms operate in an epidemic environment and internalize infections among their employees in the workplace. The model is calibrated to fit the properties of the Covid-19 epidemic. We show that firms have incentives to fight against infections and can do so very effectively by increasing teleworking and rotating employees between on-site work, teleworking, and leave. Subsidies to sick leave reduce the cost of sick workers and raise workplace infections. Furlough policies are successful in reducing infections and saving lives. Firms delay and weaken the fight against infections during economic downturns.

Keywords: Covid-19, epidemic, firm behavior, on-site work, policies, teleworking.

JEL classification: C63, D20, D21, I10, I18, L23

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1 Introduction

The ongoing Covid-19 outbreak has claimed more than 670.000 lives worldwide as of August 2020. A handful of countries reacted to this outbreak with economy-wide restrictions on production, lockdowns, increased healthcare expenditure, and substantial economic stimulus packages. Currently, these restrictions on businesses and lockdowns are being lifted in many developed economies in the face of a hefty economic downturn. There is still neither a vaccine nor a cure for Covid-19 and looser restrictions increase the risk of a continued healthcare crisis. Policymakers have to address a very important question of how to restart the economy while maintaining low levels of infections.

The risk of infections among employees and the risk of production disruptions because of this are an important challenge for firms according to surveys and quarterly earnings reports (Hassan et al., 2020). These production disruptions can reduce profitability. From public policy perspective, it is vital to formulate informed policies which can reduce the incidence of infections in firms, while keeping them afloat. For this purpose, it is important to develop a sound understanding of the behavior of firms in terms of their utilization of labor in times of an epidemic.

We derive a theoretical model in which firms operate in an epidemic environment and make choices on the allocation of their employees to maximize discounted profits. The workforce of a representative firm is comprised of productive employees who work on-site and remotely, employees who are on leave/furloughed, and employees who are on sick leave. On-site employees are more productive than employees who work remotely, but they face a higher risk of being exposed to the disease. The probability of infections among teleworking employees and employees on leave depends on the stage of the epidemic and is exogenous for the firm. In addition to this risk, on-site employees face the risk of catching infection at the workplace. The risk of an on-site employee becoming exposed to the disease is an increasing function of the number of infectious on-site employees. The firm takes this into account in its choices.

Employees with an incubated infection are infectious. As the disease progresses, they become sick either with symptoms or without them. Sick employees with symptoms are on sick leave and cannot work. They either recover or pass away. Sick employees with no symptoms are also infectious though they necessarily recover. All recovered employees are immune to a new infection. Neither the employee nor the firm knows that the employee is infectious if the employee has no symptoms.

The firm incurs several types of costs because of infections among its employees.

It pays remuneration to employees on sick leave. It also has to adjust its size in the short term because employees take sick leave and in the longer term because of death among its employees. These adjustments are costly for the firm because it has a concave production function and prefers to smooth production over time.

In this model, strategies of the firm for reducing the infections and the associated costs include allocation of employees into teleworking and leave and their rotation between on-site work, teleworking, and leave. The employees who worked on-site in the previous period have a higher probability of being infectious. Therefore, the risk of infections in the workplace can decline if the firm decides to allocate them to either teleworking or leave.

We calibrate this model to match the properties of the Covid-19 epidemic and show that the fight against infections in firms has significant effect on the dynamics of the epidemic. The choices of employee allocations and rotation in firms reduce the peak number of sick employees with symptoms by 5 percent in the benchmark simulation exercise as compared to a hypothetical scenario where firms do not fight against infections. These choices also flatten the infections curve by reducing the total number of symptomatic infections by 18 percent. The death rate also declines by 18 percent as a consequence.

Firms fight against infections in the workplace because that allows them to reduce their profit losses during the epidemic. The choices of firms also reduce output losses during the epidemic that stem from an increased number of employees on sick leave and death among employees. The gains of firms, however, are not as significant as gains from saved lives as measured by the value of statistical life, for example. This opens a scope for public policies.

In our simulation exercise a 3 percent subsidy to teleworking reduces the peak of the epidemic by about 3 percent and the total number of symptomatic infections and death rate by nearly 9 percent. It also increases the profits of firms and their output. Subsidies to sick leave payments increase infections because they reduce the willingness of firms to fight against infections. These subsidies increase the profits of the firms. However, they reduce output during the year when the epidemic started. For example, firms do not fight against infections and do not send employees to teleworking if their sick leave payments are completely eliminated. In this case, the profits of the firms during the year of the epidemic decline very modestly by 0.11 percent, which implies 7.24 percent lower fall in profits than in the benchmark simulation. Yearly output of firms declines by 2.34 percent because of the epidemic, which implies 0.17 percent higher fall in output than in the benchmark simulation. On the contrary, policies increasing sick leave payments of firms reduce infections and death. They also reduce profits, but increase output. In turn, policies completely eliminating payments to employees on leave reduce infections and death. These policies increase the profits of firms by 0.30 percent as compared to the benchmark but reduce their output by 4.75 percent during the year when the epidemic started.

Many countries have implemented lockdowns and have imposed restrictions on production during the Covid-19 epidemic. These lockdowns and production restrictions have also often served as important motivations for policies subsidizing the costs of the remuneration of employees on leave. This paper focuses on producers and their behavior and abstracts from consumers. Admittedly, consumer behavior during the epidemic can also result in reduced demand and fall in equilibrium output (see, e.g., Acemoglu et al., 2020, Brotherhood et al., 2020a, Eichenbaum et al., 2020b). We adopt a reduced form approach and model restrictions on production and changes in the demand as a fall in productivity which depends on the number of sick people. We assume that as higher the number of sick people is as stronger are the lockdown, the restrictions on production, and the fall in the demand. We select the fall in productivity in a way that the resulting fall in output is 6 percent during the year when the epidemic started as compared to the case when there is no epidemic. This is the IMF's current forecast of the fall in GDP in advanced economies for 2020.

This fall and the resulting economic downturn induce firms to fight less against infections in terms of rotation of employees between on-site work and teleworking. They also induce them to delay the fight against infections. There are a few reasons for this. In general, the gains from fighting infections are low during economic downturns because healthy workers produce less. Firms anticipate the downturn, delay shifting employees to teleworking, which is a less productive activity, and allow them to catch the disease at the workplace at the beginning of the epidemic. This increases the number of on-site infectious employees, the probability of catching the disease at the workplace, and the number of sick employees. Firms also anticipate the reversal and the economic upturn. At the beginning of the upturn, their gains from having healthy workers start increasing. Their incentives to fight infections are also high because of a high probability of catching the disease at the workplace. They start intensively fighting against infections around the beginning of the upturn in terms of allocating employees to teleworking.

This fight against infections bears larger benefits for firms when there is an economic downturn than when there are no restrictions on production, lockdown, and changes in the demand. The fight against infections allows firms to have 3.21 percentage point lower loses in terms of yearly profits and 0.85 percent lower loses in terms of output. Without this fight, their loses would be 22.19 percent in terms of profits and 6.80 percent in terms of output.

Our project contributes to the literature that combines epidemiological models with equilibrium behavioral choice. Studies in this literature have usually focused on individual choices and the negative externality that infected individuals impose on susceptible individuals by not internalizing the costs of transmission. Kremer (1996) was one of the first to study this negative externality and to show that it increases infections (see also Chen et al., 2011, Toxvaerd, 2019). A few studies have also considered the role of this externality in quantitative economic models of disease transmission (e.g., see Chan et al., 2016, Greenwood et al., 2019). Many very recent studies in this literature investigate the Covid-19 outbreak. These studies investigate a broad spectrum of issues, such as the design of optimal containment policies (Acemoglu et al., 2020, Alvarez et al., 2020, Eichenbaum et al., 2020a), the effects of testing on the evolution of the epidemic (Brotherhood et al., 2020a, Eichenbaum et al., 2020b), heterogeneous impacts of Covid-19 on the population (Alon et al., 2020, Brotherhood et al., 2020b, Favero et al., 2020, Kaplan et al., 2020), and its effects on the labor market (Kapicka and Rupert, 2020). We are the first to develop a model where firms internalize the costs of disease transmissions among their employees and fight against infections as a result. This fight reduces infections and alleviates the effects of the negative externalities. We calibrate the model to fit the properties of the Covid-19 epidemic and show that the fight against infections in firms has important quantitative implications for the dynamics of the epidemic, profits, employment, and output.

We also contribute to a group of papers that empirically investigate the effects of Covid-19 on firms by studying the incentives that firms face in during an epidemic (e.g., see Fahlenbrach et al., 2020, Ding et al., 2020, Alfaro et al., 2020, Hassan et al., 2020, Bartik et al., 2020).

The next section introduces the model. Section 3 describes our calibration strategy. Section 4 presents simulation results. Section 5 concludes.

2 Model

Time is discrete and runs forever. A representative firm makes choices on how to manage its workforce to maximize its discounted profits in an epidemic environment. The human resources of the firm are comprised of productive employees who work on-site (n) and remotely (h), employees who are on leave/furloughed (ℓ), and employees who are on a sick leave (s).

The production function of the firm has decreasing returns to scale and is given by

$$f(n,h) = A(n+\gamma h)^{\alpha}, \tag{1}$$

where $A > 0$, $\alpha \in (0,1)$, and $\gamma \in (0,1)$ is the relative productivity of teleworking employees. The instantaneous profits of the firm at time t are given by

$$\pi_t = A(n_t+\gamma h_t)^{\alpha} - \delta_n w n_t - \delta_h w h_t - \delta_\ell w \ell_t - \delta_s w s_t, \tag{2}$$

where δ_n, δ_h, δ_ℓ, $\delta_s \geq 0$, and $w > 0$ is the wage rate. The parameters δ measure the relative cost of each type of employee, and we use them to model various policies, such as subsidies to teleworking and to sick leave. The benchmark value of parameters δ is 1. The wage rate is an exogenous parameter in the model.

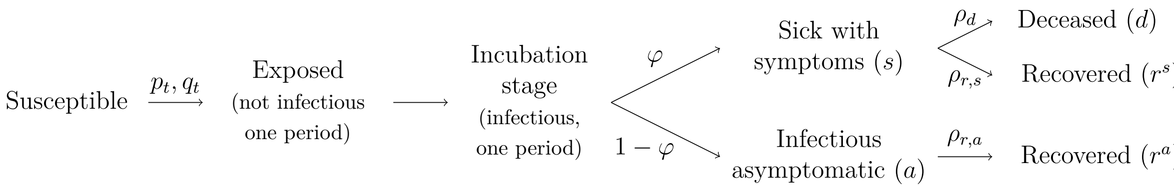
The firm does not anticipate the epidemic. It solves a static problem before the epidemic. It sets $h = 0$ since $\gamma < 1$ and chooses n to maximize its instantenous profits taking w as given:

$$\max_n An^{\alpha} - \delta_n w n. \tag{3}$$

Let N denote the solution to this problem. We assume that the firm doesn't make hiring decisions during the Covid-19 epidemic. It also does not make firing decisions even though it can keep workers on leave indefinitely.

An employee of the firm can be in either of the following states: healthy and susceptible to infection (c), exposed to infection, infectious with an incubated infection, either sick with symptoms (s) or sick without symptoms (a), and either recovered (r) or deceased (d). The exposed employees become infectious with an incubated infection in the next period. In turn, employees with incubated infection have no symptoms and become sick with symptoms or without symptoms in the next period. The exposed employees necessarily either recover or pass away. The recovered employees are immune to a new infection. Neither the employee nor the firm know that the employee is infectious if she has no symptoms. Figure 1 summarizes the health status of a worker

Figure 1: Health states



in the model as well as its transitions.

A fraction of sick employees (ρ_d) dies and a fraction of surviving sick employees ($\rho_{r,s}$) recovers in the next period, thus, adding to the pool of deceased employees (d) and to the pool of known recovered employees (r^s),

$$d_{t+1} = d_t + \rho_d s_t, \tag{4}$$

$$r^s_{t+1} = r^s_t + (1-\rho_d)\rho_{r,s} s_t. \tag{5}$$

The number of asymptomatic sick employees at time t is a_t. A fraction of them ($\rho_{r,a}$) recovers in the next period, thus, adding to the pool of recovered asymptomatic employees (r^a),

$$r^a_{t+1} = r^a_t + \rho_{r,a} a_t. \tag{6}$$

There can be employees with incubated infection among on-site, teleworking, and furloughed employees. These employees can transmit the disease. We use $\tilde{n}_t$, $\tilde{h}_t$ and $\tilde{\ell}_t$ to denote the numbers of on-site, teleworking, and furloughed employees with incubated infection time t. We use $\tilde{m}_t$ and m_t to denote, correspondingly, the number of employees with incubated infection and the number of employees with uncertain health status among teleworking and furloughed employees at time t,

$$\tilde{m}_t = \tilde{h}_t + \tilde{l}_t, \tag{7}$$

$$m_t = h_t + l_t. \tag{8}$$

The employees with incubated infection become sick in the next period and show symptoms with a probability $\varphi \in (0,1)$. The number of sick employees who show symptoms is given by

$$s_{t+1} = (1-\rho_d)\left(1-\rho_{r,s}\right) s_t + \varphi\left(\tilde{n}_t + \tilde{m}_t\right). \tag{9}$$

In turn, the number of asymptomatic sick employees is given by

$$a_{t+1} = (1 - \rho_{r,a})a_t + (1 - \varphi)(\tilde{n}_t + \tilde{m}_t). \tag{10}$$

Susceptible employees who either work remotely or are on leave become exposed to infection at time t with a probability $q_t \in [0, 1]$. The probability of infection out of the workplace depends on the stage of the epidemic and is exogenous for the firm. In addition to this risk, the susceptible on-site employees face the risk of getting infected at the workplace. The probability of infection at the workplace is a function of the number of infectious on-site employees, which are composed of employees with incubated infection ($\tilde{n}_t$) and asymptomatic sick employees ($a_{n,t}$):

$$p_t = \min \{\Pi_{p,q} q_t + \Pi_{p,n}(\tilde{n}_t + a_{n,t}), 1\}, \tag{11}$$

where $\Pi_{p,q} \geq 1$ and $\Pi_{p,n} > 0$. A susceptible on-site employee faces a higher risk of infection compared to a teleworking and furloughed employees even if there are no infectious employees in the workplace when $\Pi_{p,q} > 1$. Therefore, parameter $\Pi_{p,q}$ captures features such as the increase in the probability of infection due commuting to work. Parameter $\Pi_{p,n}$ measures how the infection risk increases with the number of infectious on-site workers, capturing characteristics such as workplace density and hygiene.

In each period, the firm decides how to manage workers who have uncertain health status and recovered symptomatic workers. Employees who have uncertain health status and worked on-site in the previous period have a higher probability of being infectious in the current period than employees who did not work on-site. Therefore, the firm splits workers with uncertain health status into those who did and did not work on-site in the previous period.

We define three groups of employees in order to characterize the choices of the firm. These groups include employees who have uncertain health status and worked on-site in the previous period (n), employees who have uncertain health status and did not work on-site in the previous period (m), and known recovered employees (r). Let k_t^i denote the number of employees in group $i \in \{n, m, r\}$ who are in situation $k \in \{n, h, \ell\}$ in time period t. For example, h_t^n denotes the number of workers who have uncertain health status, worked on-site in $t - 1$, and work remotely in t. Table 1 summarizes our notation for the choice variables of the firm.

We use this notation and write the number of sick on-site employees with no symp-

Table 1: The choices of the firm

		On-Site in t	Teleworker in t	Leave in t
Uncertain status	On-Site in $t-1$	n_t^n	h_t^n	ℓ_t^n
	Not on-site in $t-1$	n_t^m	h_t^m	ℓ_t^m
	Recovered workers	n_t^r	h_t^r	ℓ_t^r

toms as the product of the fraction of employees who are asymptomatic and the number of on-site employees with uncertain health status:

$$a_{n,t} = \frac{a_t}{N - r_t^s - s_t - d_t}(n_t^n + n_t^m). \tag{12}$$

Employees, who work on-site and are in the incubation stage at time t, were exposed to infection in $t-1$ either in the workplace or out of the workplace. The number of on-site employees in the first group is given by the number of on-site employees with uncertain health status in $t-1$ (n_t^n) multiplied by the fraction of susceptible workers in $t-1$ (c_{t-1}) times the probability of catching Covid-19 in the workplace in $t-1$ (p_{t-1}). The number on-site employees in the second group is given by the number of teleworking and furloughed employees with uncertain health status in $t-1$ (n_t^m) multiplied by the fraction of susceptible workers in $t-1$ (c_{t-1}) times the probability of catching Covid-19 out of the workplace in $t-1$ (q_{t-1}). Finally, the number of on-site employees in incubation stage is given by

$$\tilde{n}_t = n_t^n c_{t-1} p_{t-1} + n_t^m c_{t-1} q_{t-1}. \tag{13}$$

The fraction of susceptible workers in $t-1$ is given by the proportion of employees with uncertain health status who were neither sick with no symptoms nor recovered after an asymptomatic illness:

$$c_{t-1} = 1 - \frac{a_t + r_t^a}{N - r_t^s - s_t - d_t}. \tag{14}$$

An equation similar to (13) holds for the number of employees, who are either teleworking or on leave and are in incubation stage in period t:

$$\tilde{m}_t = m_t^n c_{t-1} p_{t-1} + m_t^m c_{t-1} q_{t-1}, \tag{15}$$

where $m_t^n = h_t^n + \ell_t^n$ and $m_t^m = h_t^m + \ell_t^m$.

The firm faces the following constraints in terms of its human resources:

$$n_t^n + h_t^n + \ell_t^n = n_{t-1}^n + n_{t-1}^m - \varphi \tilde{n}_{t-1}, \tag{16}$$

$$n_t^m + h_t^m + \ell_t^m = h_{t-1}^n + \ell_{t-1}^n + h_{t-1}^m + \ell_{t-1}^m - \varphi \tilde{m}_{t-1} \tag{17}$$

$$n_t^r + h_t^r + \ell_t^r = r_t^s. \tag{18}$$

The right-hand-side of equation (16) denotes the number of workers with uncertain health status who worked on-site in $t-1$ and are available to work in t. This is given by the number of on-site workers with uncertain health status in $t-1$ minus those who start showing symptoms in t. These workers can be allocated either into on-site work or teleworking or leave in t according to the left-hand side of equation (16). A similar interpretation holds for equations (17) and (18).

The firm has a discount factor $\beta \in (0, 1)$ and can exist forever. It selects the allocation of employees in on-site work, teleworking, and leave for every point in time to maximize the present discounted value of its instantaneous profits. All its dynamic constraints depend on h_t and ℓ_t through the sum of both variables m_t. This happens because teleworkers and employees on-leave face the same risk of infection, q_t. Therefore, we can write the allocation problem of the firm as a nested two-stage problem. In the first (outer) stage, the firm chooses the allocation of workers in on-site work, n_t^i for $i \in \{n, m, r\}$, and out of the workplace, m_t^i for $i \in \{n, m, r\}$, to solve the following dynamic problem

$$\begin{gathered} \max_{\{n_t^n, m_t^n, n_t^m, m_t^m, n_t^r, m_t^r\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty} \beta^t \pi_t \\ \text{s.t.} \\ (2) - (18), \end{gathered} \tag{19}$$

with $m_t^i = h_t^i + \ell_t^i$ for $i \in \{n, m, r\}$.

In the second (inner) stage, the firm allocates the employees out of the workplace between teleworking and leave in each t solving a static problem:

$$\begin{gathered} \max_{h_t, \ell_t} A(n_t + \gamma h_t)^{\alpha} - \delta_n w n_t - \delta_h w h_t - \delta_\ell w \ell_t - \delta_s w s_t \\ \text{s.t.} \\ h_t + \ell_t = m_t^n + m_t^m + m_t^r \\ n_t = n_t^n + n_t^m + n_t^r. \end{gathered} \tag{20}$$

We assume that infections start at $t = -1$, with a small number $\varepsilon > 0$ of workers in incubation stage, and that the firm could not anticipate the epidemic before $t = 0$. The initial conditions for the firm are

$$n^n_{-1} = N, \ \tilde{n}_{-1} = \varepsilon, \tag{21}$$

$$n^m_{-1} = n^r_{-1} = m^n_{-1} = m^m_{-1} = m^r_{-1} = \tilde{m}_{-1} = d_{-1} = s_{-1} = r^s_{-1} = r^a_{-1} = a_{-1} = 0. \tag{22}$$

The time path of infection probability $\{q_t\}_{t=0}^{\infty}$ is determined in equilibrium, and depends on the number of infectious workers in the economy. At time t, this probability is given by

$$q_t = \Pi_q(\tilde{n}_t + \tilde{m}_t + a_t), \tag{23}$$

where $\Pi_q > 0$ is a parameter that measures the transmission rate of Covid-19.

Definition of Equilibrium: The equilibrium consists of time paths of the number of susceptible, incubated, symptomatic and asymptomatic sick, recovered, and deceased employees, $\{c_t, \tilde{n}_t, \tilde{m}_t, s_t, a_t, r^s_t, r^a_t, d_t\}_{t=0}^{\infty}$, labor force allocations, $\{n^i_t, h^i_t, \ell^i_t\}_{t=0}^{\infty}$ for $i \in \{n, m, r\}$, and infection probabilities $\{q_t, p_t\}_{t=0}^{\infty}$, such that:

1. Taking the sequence $\{q_t\}_{t=0}^{\infty}$ as given, the representative firm chooses labor allocations to solve problem (19) and (20).

2. The firm's choices and the law of motions give rise to the sequences $\{p_t, q_t\}_{t=0}^{\infty}$ and the distribution of workers across health states.

This model has a few notable and intuitive features. The epidemic has negatives effects on the output and profits of the firm. The workforce of the firm shrinks during the epidemic because employees catch infection and take a sick leave. This reduces the output and profits since $\delta_s > 0$ and the firm cannot achieve its optimal size given by the solution of static problem (3). The workforce of the firm is also smaller after the culmination of the epidemic because of deaths among workers. This also reduces output and profits.

The firm allocates all known recovered employees into on-site work given that $\gamma < 1$. It has incentives to increase the number of teleworking employees in times of an epidemic because that reduces the probability of infections among on-site employees, p_t, and infections among all employees given that $p_t \geq q_t$. For the same reasons, it can have an incentive to increase the number of employees on leave during an epidemic. The firm incurs loses in terms of current profits when it allocates employees into teleworking and leave but reduces future profit loses which stem from sick leave payments and adjustments in the size of the workforce. It also has incentives to rotate employees between on-site work and either teleworking or leave because employees who were working on-site previously have higher chances of being infectious than employees who were either teleworking or on leave in previous periods. All these incentives are stronger for higher values of the ratio p_t/q_t.

The choices of the firm are also influenced by the values of δ_n, δ_h, δ_ℓ, and δ_s, which we treat as policy parameters. For example, on-site work can be restricted and more costly to carry during a lockdown. We assume that lockdowns can increase the value of δ_n and that increases the costs of carrying on-site work in the firm. An increase in the value of δ_n amplifies the incentives of the firm to allocate employees into teleworking. Subsidies to teleworking have a similar effect on the incentives of the firm. We model such subsidies as a reduction in the value of δ_h. Schemes that reduce the costs of employment adjustments can be represented as reductions in the value of δ_ℓ because a lower value of δ_ℓ implies a lower cost of sending employees to leave and adjusting the size of the workforce and production. In turn, subsidies for the remuneration of employees on sick-leave can be represented as a reduction in the value of δ_s. The latter two policies can reduce the costs of the firm. However, for example, a lower value of δ_s also reduces the incentives of the firm to fight infections because it reduces the cost of infections for the firm.

3 Calibration

We interpret the model period as being one week and select a value for the time discount parameter β such that annual time discounting is equal to 0.96. We normalize the value of productivity parameter A to 1 and set $\alpha = 0.7$, which implies that the share of labor force compensation in an environment with no disease/epidemic is 0.7. We set wage rate so that the optimal size of the firm is equal to 1 in such an environment. This implies that $w = 0.7$.

We choose a value for the relative productivity of teleworkers γ in a way that the firm chooses 30 percent of its labor force to be teleworkers at the peak of the epidemic in the benchmark equilibrium. Brynjolfsson et al. (2020) conduct a survey among workers in the U.S. and find that 32 percent of the interviewed individuals were teleworkers on April 1, 2020, but used to commute to work before the Covid-19 outbreak.

The benchmark equilibrium is defined as the situation with no government policy, so that all δ parameters are equal to one. Table 2 summarizes the values of all these

Table 2: Calibration of parameters

Parameter	Value	Comment
Panel A. Firm		
A	1	Normalization
N	1	Normalization
α	0.7	Labor share of revenues
β	$0.96^{1/52}$	Time discount
γ	0.9	$\approx 30\%$ teleworkers at peak (Brynjolfsson et al., 2020)
w	0.7	Wage is such that optimal $N = 1$ in no disease/epidemic times
δ_n	1	Policy parameter
δ_h	1	Policy parameter
δ_ℓ	1	Policy parameter
δ_s	1	Policy parameter
Panel B. COVID-19		
$\rho_{r,s}$	1/3.52	Average duration of hospitalization (Verity et al., 2020)
$\rho_{r,a}$	1/3.52	Same as $\rho_{r,s}$
ρ_d	0.00202	Probability of death conditional on hospitalization (CDC, 2020)
Π_q	0.25	$R_0 = 2.5$
$\Pi_{p,q}$	1	No discontinuity from q to p
$\Pi_{p,n}$	0.6667	$\approx 70\%$ of infections in the workplace (Ferguson et al., 2006)
φ	0.5	Prop. asymptomatic, range: 4%-75% (CEBM, 2020)
ε	0.001	0.1% infected workers in first period

parameters.

Regarding the parameters related to Covid-19, Verity et al. (2020) find that the mean duration of hospitalization among infected patients who were discharged is equal to 3.52 weeks. We set $\rho_{r,s} = 1/3.52$ to match this. We assume that the average duration that an asymptomatic individuals stays infectious is the same as that of a symptomatic person, $\rho_{a,r} = \rho_{s,r}$. According to CDC (2020), the probability of death of a hospitalized patient with Covid-19 is 0.202%, so we set $\rho_d = 0.00202$.

The estimates of the fraction of asymptomatic individuals who caught Covid-19 are highly imprecise and range from 4% to 75% (CEBM, 2020). We set $\varphi = 0.5$, which implies that the numbers of asymptomatic and symptomatic sick individuals are equal in the model. We assume that the probability of a on-site employee catching Covid-19 if there are no infected on-site employees is the same as that of an employee catching

Covid-19 out of the workplace, yielding $\Pi_{p,q} = 1$.

According to Ferguson et al. (2006), 70% of the influenza transmissions occur outside of the household. We calibrate $\Pi_{p,n}$ such that 70% of the transmissions in the benchmark equilibrium happen in the workplace. In turn, the value of Π_q is chosen so that the basic reproduction number (R_0) of Covid-19 in our simulations is equal to 2.5. This falls in within the range of the estimates of R_0 for Covid-19, from as low as 1.6 to as high as 4 (e.g., see Zhang et al., 2020, Remuzzi and Remuzzi, 2020). As an initial condition for the infection, we start with 0.1% infected workers in $t = -1$.

4 Simulations

The data about the Covid-19 epidemic and its economic impact are still scarce, and wide ranges are reported for the available data. For example, the true fatality rates are hard to compute because it is yet unclear what fraction of the population is already infected. We also know very little about infections in and out of workplaces. We have thus used a limited set of calibration targets while omitting some important dimensions. Accordingly, a word of caution is in order regarding the interpretation of our quantitative results.

The number of new infections becomes negligible after a year in all our simulations because of herd immunity. We assume that the disease entirely disappears by the end of the third year.[1] This implies that the firm has a static problem after the third year and selects to have no teleworking employees given that $\gamma < 1$.

4.1 Benchmark equilibrium

Our benchmark simulation uses parameter values from Table 2. We present the results in the first column of Table 3 and in Figure 2 and Figure 3. It takes 14 weeks to the peak of infections. About 18 percent of the population is infected at the peak and 9 percent has symptoms. The disease infects 77.52 percent of the population during its course. Out of this number, 77.25 percent recover and the remainder pass away.

The firm puts a fight against infections. It increases the percentage of teleworking employees making it greater than zero, which is the value in normal times. As illustrated in Figure 3, these adjustments are slow at the beginning. The firm reacts to the

[1]The disease can also disappear earlier than by the end of the third year if a vaccine becomes available. This is straightforward to consider in this setup.

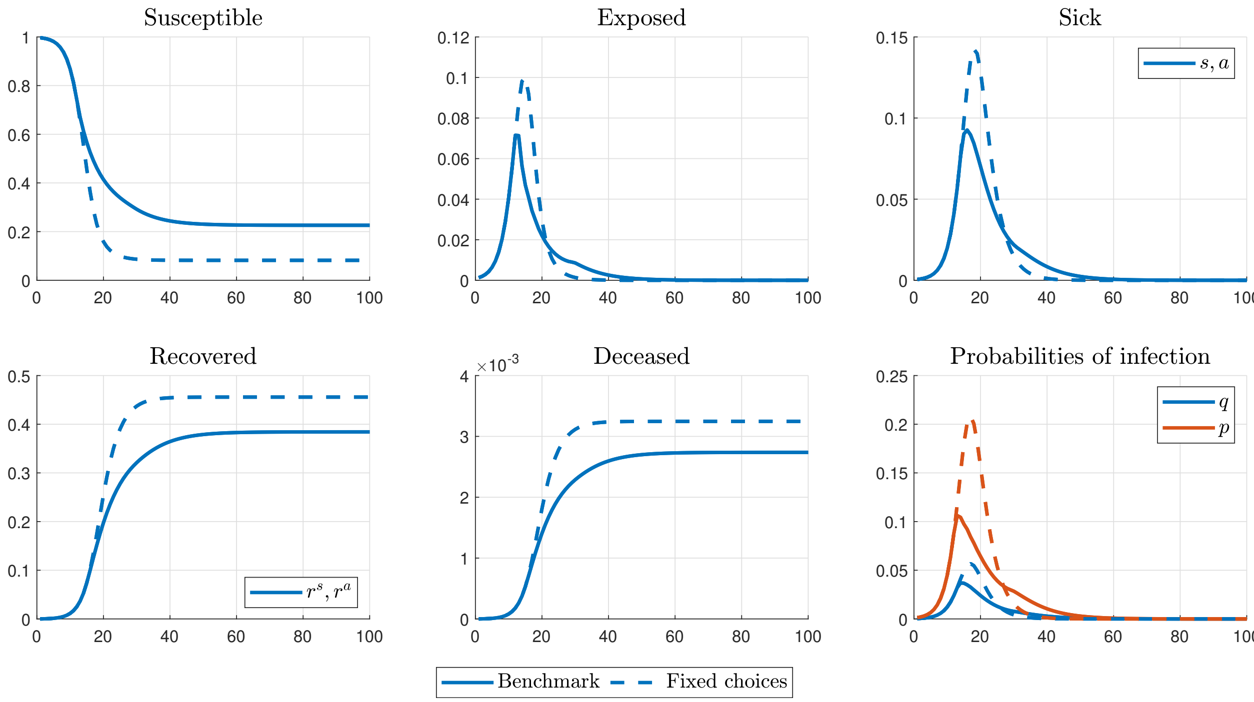
Table 3: Main results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Fixed	Teleworking		Sick leave			Leave	
	Benchmark	choices	$\gamma = 0.98$	$\delta_h = 0.97$	$\delta_s = 0.5$	$\delta_s = 0$	$\delta_s = 1.5$	$\delta_\ell = 0.5$	$\delta_\ell = 0$
Weeks to the peak	14	17	15	15	16	17	14	14	16
Sick at the peak (%)	9.31	14.25	5.95	6.04	13.56	14.25	7.15	9.31	7.58
Deceased (%)	0.27	0.32	0.25	0.25	0.32	0.32	0.26	0.27	0.26
Deceased (%Δ w.r.t. BM)	0	18.41	-8.73	-8.82	17.09	18.41	-5.64	0	-5.53
Recovered (%)	77.25	91.47	70.50	70.44	90.45	91.47	72.89	77.25	72.98
Recovered (%Δ w.r.t. BM)	0	18.41	-8.73	-8.82	17.09	18.41	-5.64	0	-5.53
Production 1 year (%Δ w.r.t. ND)	-2.17	-2.34	-1.83	-2.12	-2.32	-2.34	-2.13	-2.17	-6.81
Production 1 year (%Δ w.r.t. BM)	0	-0.17	0.34	0.05	-0.16	-0.17	0.04	0	-4.75
Discounted profits	381.24	381.17	381.31	381.31	381.72	382.28	380.78	381.24	381.27
Discounted profits (%Δ w.r.t. ND)	-0.28	-0.29	-0.26	-0.26	-0.15	0	-0.40	-0.28	-0.27
Discounted profits (%Δ w.r.t. BM)	0	-0.02	0.02	0.02	0.13	0.27	-0.12	0	0.01
Profits 1 year (%Δ w.r.t. ND)	-6.85	-7.32	-5.81	-5.83	-3.71	-0.11	-9.54	-6.85	-6.58
Profits 1 year (%Δ w.r.t. BM)	0	-0.50	1.12	1.10	3.37	7.24	-2.89	0	0.30
Max. teleworking (%)	29.26	0	33.51	33.65	8.44	0	33.35	29.26	24.06
Max. leave (%)	0	0	0	0	0	0	0	0	12.05
Max. n to m (%)	29.26	0	33.51	33.65	8.44	0	33.35	29.26	31.02
Max. m to n (%)	28.28	0	32.70	32.77	7.89	0	32.39	28.28	30.12
Sum n to m	3.32	0	7.23	7.12	0.18	0	5.29	3.32	5.94
Sum m to n	3.23	0	7.12	7.01	0.17	0	5.19	3.23	5.84

Note: This table summarizes our main results from simulations. Sick at the peak (%) excludes sick with no symptoms. The percentage of sick with no symptoms is equal to the percentage of sick with symptoms since $\varphi = 0.5$. Recovered (%) includes sick with and with no symptoms. Column 1 reports the results when we use the benchmark (BM) parameter values from Table 2. Column 2 reports the results when the firm does not take into account infections among its employees and keeps the shares of labor force allocations fixed and equal to the case when there is no disease (ND). Column 3 reports the results for a higher value of $\gamma = 0.98$. Columns 4-9 report the results for various values of parameters δ_s and δ_ℓ. BM stands for the benchmark in rows 4, 6, 8, 11 and 13. ND stands for the no disease in rows 7, 10 and 12.

ongoing epidemic at week 13, close to the peak of infections. However, it reacts strongly and allocates almost 30 percent of its employees to teleworking by the time infections reach their peak. The firm also starts rotating employees between on-site work and teleworking, which can be clearly seen in terms of transitions between m and n in Figure 3.

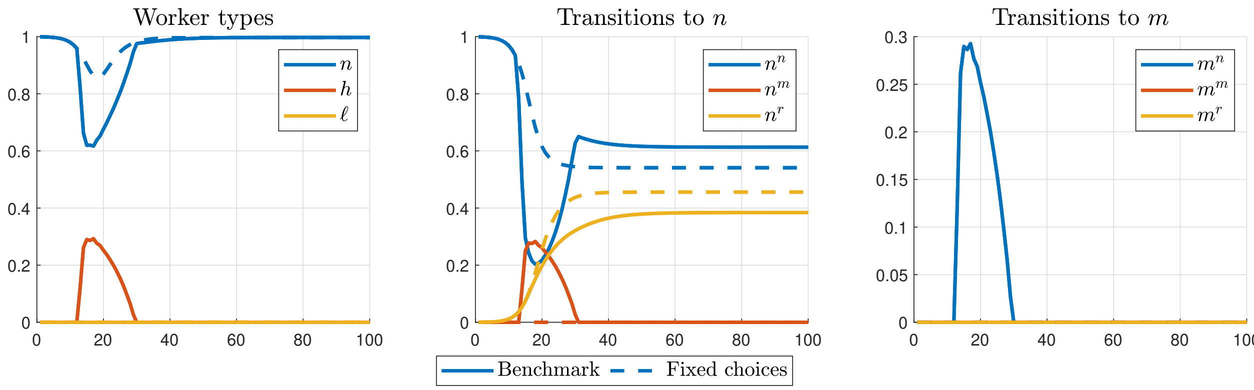
Figure 2: The dynamics of the epidemic



Note: This figure shows the dynamics of the epidemic in the benchmark model (solid lines). It also shows the difference between these dynamics and the dynamics of epidemic in a hypothetical scenario where the firm does not take into account infections among its employees and keeps its choices of allocations fixed and equal to allocations in an environment where there is no disease (dashed lines). The graphs for s and a and r^s and r^a coincide because $\varphi = 0.5$ and there are equal numbers of symptomatic and asymptomatic employees.

The output of the firm declines by 2.17 percent during the first year of the epidemic as compared to the normal environment where there has been no disease. The reduction of the output is because the employees take a sick leave, teleworking is less productive than on-site work, and some workers pass away. The profits and net present value of the firm also decline as compared to the normal environment. The profits during the first year of the epidemic decline by 6.85 percent, while the value of the firm declines more modestly by 0.28 percent.

Figure 3: The dynamics of employee allocations during the epidemic



Note: This figure shows the allocations of employees into on-site work, teleworking and leave in the benchmark model where the firm takes into account infections among their employees (solid lines). It also shows the choices of the firm regarding the rotation of employees between on-site work, teleworking and leave. It compares these dynamics with the dynamics of allocations in a hypothetical scenario where the firm does not take into account infections among its employees and keeps its choices of allocations fixed and equal to allocations in an environment where there is no disease (dashed lines).

We compare these results with the results from a hypothetical scenario where the firm does not internalize infections among its employees in the workplace. In such a case, the firm does not fight against infections. It keeps the shares of labor allocations fixed and equal to the shares of allocations in the normal environment even though death reduces the total number of available workers. Column 2 of Table 3 presents the results from the model with fixed shares of labor allocations. It takes takes 17 weeks to the peak of infections in this model. About 14 percent of employees are sick and have symptoms at the peak of infections, a 5 percentage points increase from the benchmark value. About 18 percent more employees become sick with symptoms and pass away over the course of the epidemic in case when the firm does not fight against infections as compared to the benchmark. The choices of the firm and its fight against infections have significant effects on the dynamics of the epidemic and they flatten the infection curve.

The firm gains about a half a percent of its yearly profits by fighting infections in the workplace. It gains 0.02 percent in terms of present discounted value of profits. These gains seem to be modest and there are a few reasons for that. The discounted profits are large, and the disease neither has a very long life-span nor it has a very large death toll.

The firm also incurs loses when it increases teleworking given that $\gamma < 1$. In column

3 of Table 3, we consider the case when $\gamma = 0.98$. Such a higher γ can be a result of, for example, the firm investing in improvements in teleworking practices and technologies and general improvements in information and communication technologies and their more widespread availability. It is less costly for the firm to allocate employees in teleworking with a higher γ and profits, teleworking, and the rotation of employees increase because of this. The firm gains about 1.8 percent of its yearly profits by fighting against infections in the workplace when $\gamma = 0.98$. About 36.5 percent of its employees are teleworking at the peak. The number of symptomatic infections and death during the epidemic decline by 10 percent as compared to the benchmark. Symptomatic infections at the peak decline by 4 percentage points.

Gains from fighting infections can seem to be modest at the firm level in the benchmark results. The results suggest they can be significant at the aggregate level though. The fight against infections saves 0.17 percent of the GDP in the benchmark results. This implies that the gains from this fight can be at the order of 40 billion U.S. dollars in a country like the U.S., where GDP in 2019 was 21.5 trillion. These gains are almost 3 times higher for a larger value of $\gamma = 0.98$.

The fight against infections also reduces the severity of the epidemic in terms of infections and it saves lives. The latter can be important for the firms since death inflicts a cost on firms by reducing the workforce and their production. However, this is not very important for the net present value of firms. One way to gauge the economic magnitude and significance of these numbers uses the value of statistical life. The value of statistical life in the U.S. is about \$9 million according to the most recent estimates (e.g., see U.S. Department of Transportation, 2016, U.S. Environmental Protection Agency, 2010).[2] This implies that firms can save around \$1.5 trillion in the U.S. by their actions. However, these benefits will not be directly appropriated by firms, which creates a scope for public policies. For example, the higher value of $\gamma = 0.98$ implies additional lives saved and the statistical gains from that are at the order of additional \$600 billion. The direct gains of firms in terms of profits from the higher value of γ are much lower.

4.2 Policies

We have focused on producers and their welfare and abstracted from consumer behavior and welfare in this model. In this sense, our policy exercises have a positive perspective,

[2] Viscusi and Aldy (2003) offer a review of the literature on the value of a statistical life.

and we abstract from their normative implications.

Policies that encourage teleworking and discourage on-site work have been very popular in almost all countries during the Covid-19 epidemic. In the model, policies that make on-site employment more costly for firms and subsidize teleworking increase δ_n and reduce δ_h. These are equivalent and similar to an increase in γ for the choices of labor allocation of the firm. They have a different effect on profits though as a higher δ_n reduces profits and a lower δ_h can increase them. We consider subsidies to teleworking equivalent to an increase in γ from the benchmark value to 0.98, the value in column 3 of Table 3. Column 4 of Table 3 presents the results. It is enough to subsidize teleworking by 3 percent to achieve significant reductions in peak infections, total infections, and death.

We consider policies that subsidize the costs that firms incur paying remuneration to employees on sick leave. Employees that have symptoms recover with a probability of almost 1 by the sixth week in the model. In Germany, for example, firms usually pay regular wages for six weeks to employees on sick leave. Germany allowed firms to claim back from the government their sick leave payments during the Covid-19 epidemic.[3]

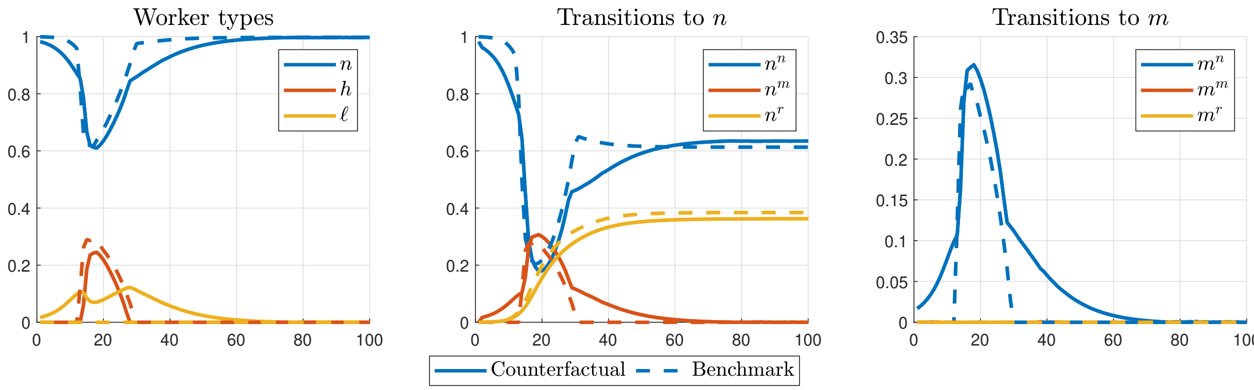
We offer the results from the implementation of a policy that halves the costs that the firm incurs paying employees on sick-leave in column 5 of Table 3 and eliminates these costs in column 6. This policy increases the profits of the firm and its value. However, it reduces the incentives of the firm to fight infections. Teleworking and the rotation of employees between on-site work and telework decline. As compared to the benchmark, this significantly increases infections in the economy, death tall of the epidemic, and reduces production during the year of the epidemic because a larger number of workers get infected and go for a sick-leave. The firm does not fight against infections at all when the policy completely eliminates sick leave costs.

We consider an alternative policy that increases the costs that the firms incur when they pay employees on sick leave. Column 7 of Table 3 presents the results when we set $\delta_s = 1.5$. This policy reduces the profits of the firm and its value as compared to the benchmark but it improves the incentives of the firm to fight infections and increases its output. The death tall of the epidemic and the total number of symptomatic infections decline by 5.64 percent as the percentage of teleworking employees and the rotation of employees between on-site work and teleworking increase.

We also consider a policy which subsidizes/reduces the costs that firms incur paying the remuneration of employees on leave. Analogous policies have been implemented,

[3]See Families First Coronavirus Relief Act, H.R. 6201 for the U.S.

Figure 4: The dynamics of employee allocations during the epidemic when $\delta_\ell = 0$



Note: This figure shows the dynamics of allocations of employees into on-site work, teleworking and leave in case when $\delta_\ell = 0$ (solid lines). It also compares these dynamics with the dynamics allocations of employees in the benchmark model (dashed lines).

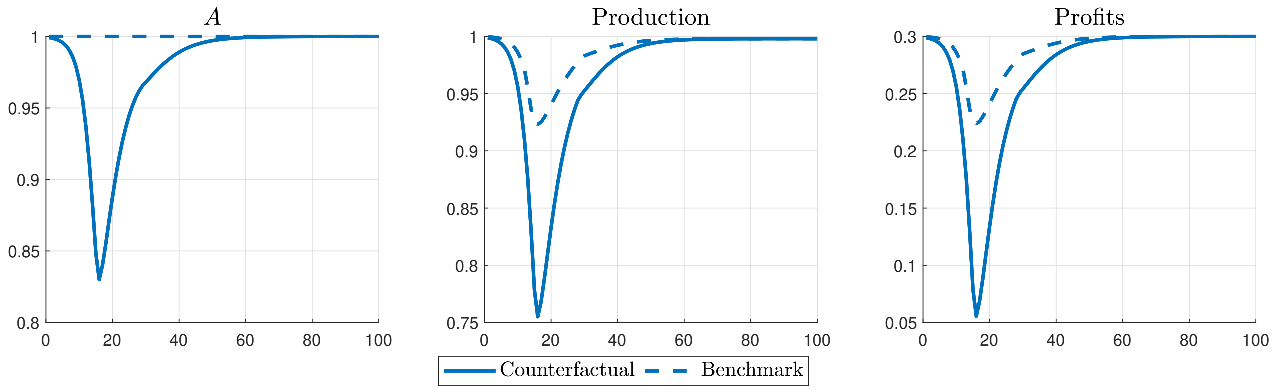
for example, in Spain with the motivation to allow firms to temporarily adjust their size. The policy halves these costs in column 8 of Table 3 and completely eliminates them in column 8. The policy has no effect on the behavior of the firm and the dynamics of the epidemic when it halves these costs. It affects them though when it completely eliminates these costs. The firm sends some employees to a temporary leave, reduces teleworking, and increases its yearly profits by 0.32 percent as compared to the benchmark. The firm also rotates employees between on-site work and teleworking and leave and increases the rotation as compared to the benchmark. Figure 4 illustrates the dynamics of employee allocations in this case. All this results in 1.73 percent lower symptomatic infections at the peak and 5.53 percent lower total symptomatic infections and death toll during the epidemic relative to the benchmark. However, it also results in 5 percent lower output relative to the benchmark.

4.3 Simulations with changes in A

Thus far, we have abstracted from lockdown policies, production restrictions, and changes in the demand for goods during the epidemic that can be a result of both lockdown restrictions as well as consumer behavior. In many countries, these have served as important motivations for implementing and enacting policies that subsidize the costs of the remuneration of employees on temporary and sick leave.

We take a reduced form approach for modeling production restrictions, lockdowns, and changes in consumer demand since we do not have consumers and their demand

Figure 5: The dynamics of A, production, and profits



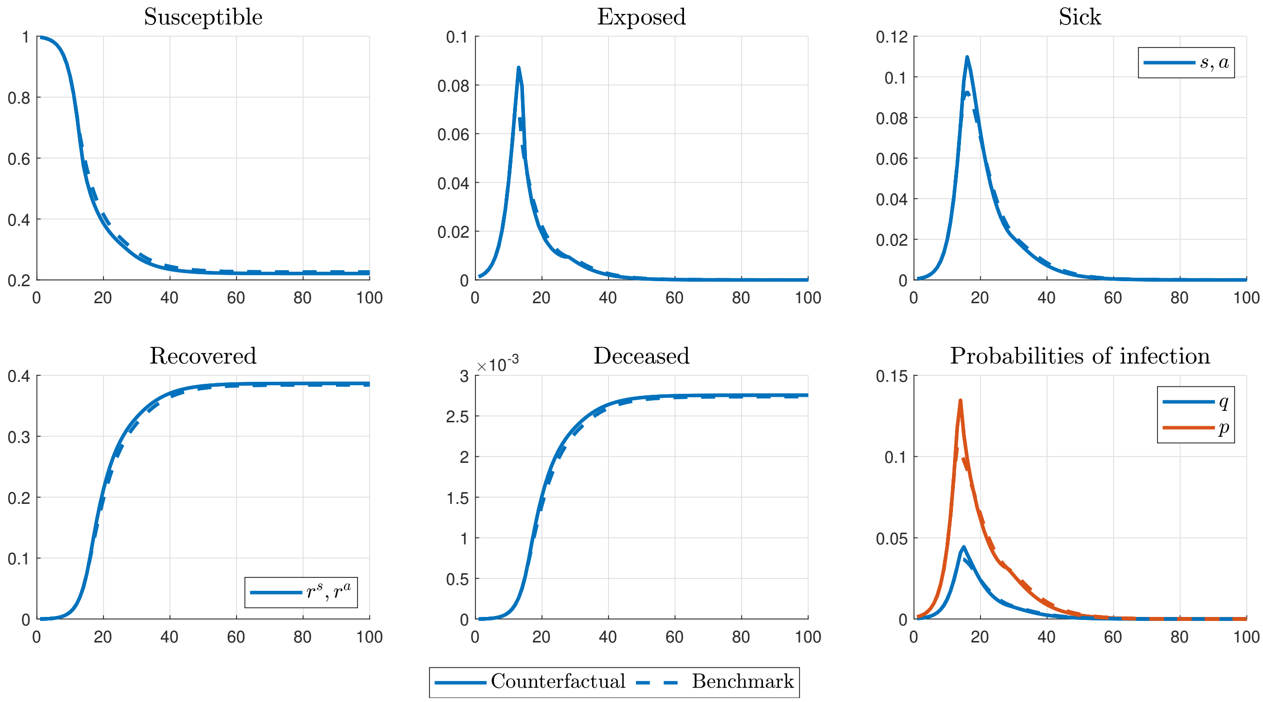
Note: This figure shows our assumed dynamics of A and the resulting dynamics of production and profits (solid lines). It also shows the dynamics of production and profits in the benchmark economy where there are no changes in A (dashed lines).

functions in this supply side framework. We assume that the strength of production restrictions and lockdown are positively correlated with the number of symptomatic sick people s and consumer demand is negatively correlated with it. We also assume that production restrictions and the fall in the demand during the epidemic because of lockdown and consumer behavior correspond to a fall in A. Finally, we assume that $A_t = 1 - \delta_A s_t$ and select the value of δ_A such that the resulting fall in output during the year of the epidemic as compared to an environment with no epidemic is about 6 percent. This is the forecast of the IMF for the fall in GDP in advanced economies in 2020 though there is a lot of uncertainty around this number. In reality, the deep of the shock can be bigger and the time to recovery can be longer according to the forecasts of the OECD (OECD, 2020).

Figures 5 and 6 show the dynamics of A, output and profits of the firm, and dynamics of the epidemic. Figure 7 shows the dynamics of the allocations of employees. Table 4 summarizes the results.

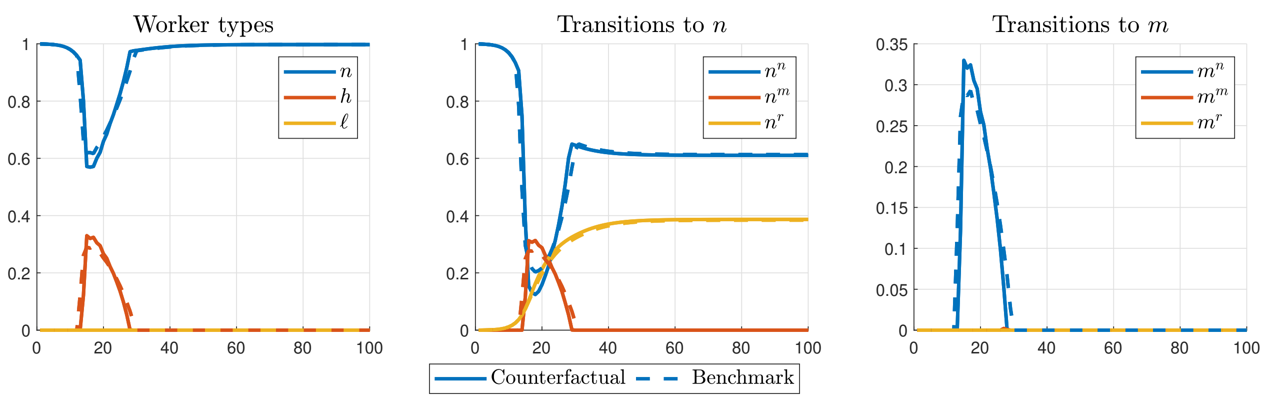
According to column 1 of Table 4, teleworking slightly increases at the peak and the rotation of employees declines because of the shock to A as compared to the benchmark in Table 3. Profits in the year of epidemic decline by 19.61 percent and output declines by 6 percent as compared to an environment where there is no disease/epidemic. The firm gains more from the fight against infections in terms of profits and output when there is a fall in A as compared to the benchmark. This can be clearly seen by comparing columns 1 and 2 in Table 3 and Table 4.

Figure 6: The dynamics of the epidemic with changes in A



Note: This figure shows the dynamics of epidemics in case when A changes as illustrated in Figure 5 (solid lines). It compares these dynamics with the dynamics allocations of employees in the benchmark model where there are no changes in A (dashed lines). The graphs for s and a and r^s and r^a coincide because $\varphi = 0.5$ and there are equal numbers of symptomatic and asymptomatic employees.

Figure 7: The dynamics of employee allocations during the epidemic with changes in A



Note: This figure shows the dynamics of allocations of employees into on-site work, teleworking and leave in case when A changes as illustrated in Figure 5 (solid lines). It compares these dynamics with the dynamics allocations of employees in the benchmark model where there are no changes in A (dashed lines).

Table 4: Results for a fall in A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Benchmark with	Fixed		Sick leave			Leave and sick leave			
	changes in A	choices	δ_n	$\delta_s = 0.5$	$\delta_s = 0$	$\delta_s = 1.5$	$\delta_\ell = 0.5$	$\delta_\ell = 0.05$	$\delta_\ell = 0$	$\delta_\ell = \delta_s = 0$
Weeks to the peak	15	17	15	17	17	14	15	15	17	16
Sick at the peak (%)	10.99	14.25	10.33	14.25	14.25	8.26	10.97	8.13	5.81	7.61
Deceased (%)	0.28	0.32	0.27	0.32	0.32	0.26	0.28	0.27	0.24	0.27
Deceased (%Δ w.r.t. BM)	0	17.81	-2.77	17.81	17.81	-6.13	-0.04	-1.89	-11.34	-3.12
Recovered (%)	77.64	91.47	75.49	91.47	91.47	72.88	77.61	76.18	68.84	75.22
Recovered (%Δ w.r.t. BM)	0	17.81	-2.77	17.81	17.81	-6.13	-0.04	-1.89	-11.34	-3.12
Production 1 year (%Δ w.r.t. ND)	-6.00	-6.80	-5.86	-6.80	-6.80	-5.66	-6.00	-10.52	-15.54	-11.83
Production 1 year (%Δ w.r.t. BM)	0	-0.85	0.15	-0.85	-0.85	0.36	0	-4.81	-10.15	-6.21
Discounted profits	379.26	378.88	379.18	379.44	379.99	378.91	379.26	379.37	379.65	380.45
Discounted profits (%Δ w.r.t. ND)	-0.79	-0.89	-0.82	-0.75	-0.60	-0.89	-0.79	-0.76	-0.69	-0.48
Discounted profits (%Δ w.r.t. BM)	0	-0.10	-0.02	0.05	0.19	-0.09	0	0.03	0.10	0.31
Profits 1 year (%Δ w.r.t. ND)	-19.61	-22.19	-20.00	-18.59	-14.98	-21.31	-19.61	-18.79	-16.16	-11.86
Profits 1 year (%Δ w.r.t. BM)	0	-3.21	-0.48	1.28	5.77	-2.11	0.01	1.02	4.30	9.65
Max. teleworking (%)	32.65	0	40.54	0	0	35.05	33.58	2.18	0	0
Max. leave (%)	0	0	0	0	0	0	0	27.90	30.36	26.26
Max. n to m (%)	32.65	0	40.54	0	0	35.05	33.58	28.08	30.36	26.26
Max. m to n (%)	31.20	0	37.51	0	0	33.97	32.16	27.17	29.63	25.05
Sum n to m	3.09	0	3.84	0	0	5.02	3.09	3.86	9.16	4.60
Sum m to n	3.00	0	3.75	0	0	4.92	3.01	3.77	9.05	4.51

Note: This table summarizes our main results from simulations where we consider changes in A. These changes are summarized in Figure 5. Column 1 reports the results when we use the benchmark parameter values from Table 2 with an exception that we vary A (BM). Column 2 reports the results when the firm does not take into account infections among its employees and keeps the shares of labor force allocations fixed and equal to the case when there is no disease (ND). Column 3 reports the results when we change the value of δ_n. We assume that δ_n increases from 1 up to a peak value of 1.02 as A declines and reaches its minimum and it declines to its original value as A increases. Columns 4, 5, and 6 report the results when we vary the value of δ_s. Columns 7, 8, and 9 report the results when we vary the value of δ_ℓ. We set δ_s and δ_ℓ equal to zero in column 10.

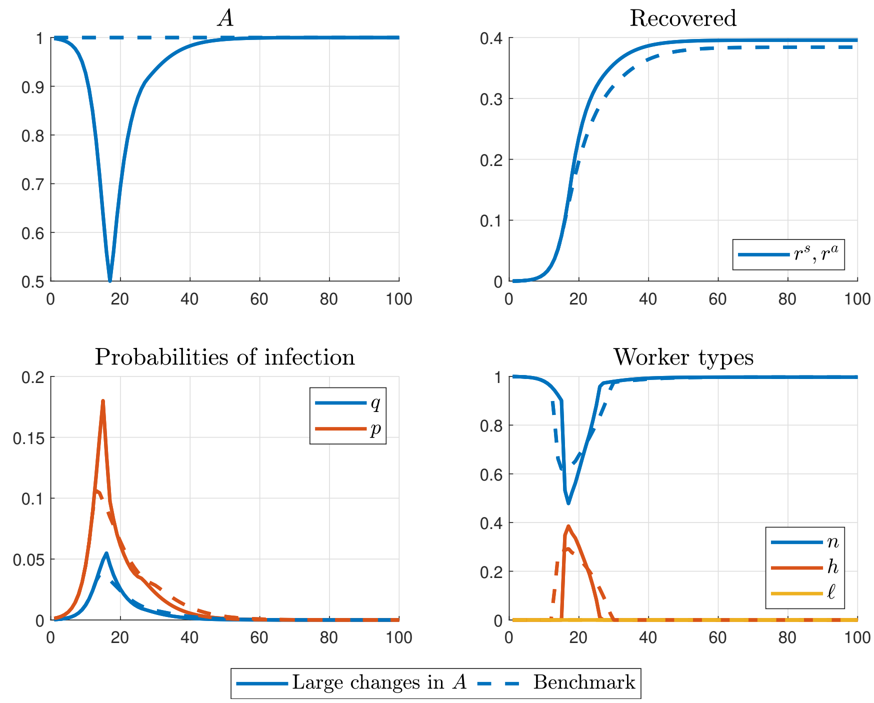
The disease infects 77.92 percent of the population during its course. Symptomatic sick at the peak are 10.99 percent. These numbers are higher than the benchmark values in column 1 of Table 3.

There are a few forces that are responsible for these results. The incentives of the firm are driven by its anticipation of the trajectory of A. The static trade-off between on-site work n and teleworking h is fixed and does not depend on A. The marginal cost of sick leave $\delta_s w$ also does not depend on A. Meanwhile, the marginal products of n and h simultaneously fall as A declines. This implies that the gains from fighting infections are low for lower values of A. The firm anticipates the fall in A and is reluctant to fight against infections at the beginning of the epidemic because of this. It delays sending employees to teleworking and reacts less strongly at the beginning, which increases the probability of infections at the workplace and the number of infections, exposed and sick. The firm also anticipates the reversal and the economic upturn. At the beginning of the upturn, its gains from having healthy workers start increasing. Its incentives to fight infections are also high because of the high probability of catching the disease at the workplace. These incentives are negatively affected by the "herd immunity", however. The number of recovered and immune workers is higher because the firm has put less effort in fighting infections at the beginning of the epidemic. This makes the ongoing epidemic less costly for the firm and reduces its incentives to allocate employees to teleworking and rotate them. With the current parameterization, all these effects imply a slightly higher number of teleworking employees at the peak. We consider a much larger shock to A in order to illustrate these dynamics more vividly. Figure 8 offer the results.

Lockdown policies can also increase the costs of on-site employment, which corresponds to an increase in δ_n. We assume that changes in δ_n are in the opposite direction to changes in A, so that δ_n increases at the beginning of the epidemic to 1.02 and declines to its original value of 1 afterwards as A increases. Column 3 of Table 4 offer the results when both A and δ_n change. These changes in δ_n imply higher losses in terms of yearly profits, but slightly lower losses in terms of output. The latter result holds because there are less infections and a lower number of workers demand sick leave in this case.

Similarly to the results in Table 3, policies that reduce the value of δ_s increase the profitability of the firm at the expense of production and infections and death among workers. Columns 4 and 5 of Table 4 offer the results when we reduce the costs of sick leave by half and set $\delta_s = 0.5$ and completely eliminate these costs by setting $\delta_s = 0$. In

Figure 8: Large changes in A



Note: This figure shows the dynamics of recovered and p and q when we consider a relatively large fall in A (solid lines). It compares these dynamics with the dynamics allocations of employees in the benchmark model where there are no changes in A (dashed lines). The graphs for r^s and r^a coincide because $\varphi = 0.5$ and there are equal numbers of symptomatic and asymptomatic employees.

both cases, the firm does not fight against infections and the epidemiological results are similar to the case when the firm keeps its choices of labor allocations fixed in column 2 of Table 4. Policies that increase the value of δ_s have the opposite effect according to column 5 of Table 4. A policy that mandates firms to pay 50 percent more to employees on sick leave and sets $\delta_s = 1.5$ significantly intensifies the fight against infections. It increases teleworking and rotation of employees and reduces infections and death as a result. It also further reduces yearly profits by 2.11 percent but alleviates the fall in output. The fall in output is 5.66 percent instead of 6 percent with this policy.

Policies that reduce the costs of sending employees on leave δ_ℓ can slightly increase profits but can reduce employment and significantly contribute to the recession during the year of the epidemic according to columns 7, 8, and 9 of Table 4. We attempt to mimic minimal employment adjustment costs and consider a small positive value $\delta_\ell = 0.05$ in column 8. This produces a fall in output of 10.52 percent during the epidemic and an increase in temporary unemployment of up to 27.90 percent at the peak of the epidemic. The magnitudes of these adjustments resemble the adjustments and their forecasts in Spain which enacted a policy to reduce employment adjustment costs at the beginning of the Covid-19 epidemic.

The reduction of employment adjustment costs also significantly affects the dynamics of the epidemic when A declines. The infections curve significantly flattens as the peak of the infections and the total number of infections decline.

Many countries have put an aggressive fight against the Covid-19 epidemic in an attempt to alleviate its economic impact by implementing a number of policies at the same time. In column 10 of Table 4, we consider a case when the policies eliminate payments of the firm to all employees on leave and set $\delta_s = \delta_\ell = 0$. Such a policy considerably reduces the fall in profits. It also reduces the fall in output as compared to the case when only $\delta_\ell = 0$. The reason for this is that the firm incurs lower costs and has a lower number of employees on leave when $\delta_s = \delta_\ell = 0$. It continues rotating employees between on-site work and leave because that reduces infections, the number of employees on sick leave, and implied changes in the number of available workers. The peak of infections and the total number of infections though grow as compared to column 9.

5 Conclusions

We derive a model in which a representative firm operates in an epidemic environment. The workforce of the firm is comprised of productive employees who work on-site and remotely, employees who are on leave/furloughed, and employees who are on sick leave. On-site employees are more productive than employees who work remotely, but they face a higher probability of catching the disease. The infections among employees are costly for the firm. The firm chooses the allocation of its employees into on-site work, teleworking, and leave, and rotates them to maximize its discounted profits. It takes into account how its choices affect infections in the workplace.

We calibrate this model to match the properties of the Covid-19 epidemic. Our simulation results show that the fight against infections in firms has significant effect on the dynamics of the epidemic. It flattens the infections curve by reducing the total number of symptomatic infections by 18 percent and the peak of the epidemic by 5 percent. As a consequence, the death rate declines by 18 percent as well.

This fight bears benefits for the firms in terms of profits and output albeit these gains might not be large. Gains as measured, for example, by the value of statistical life are an order of magnitude higher, which can create a scope for public policies.

In our simulations, policies subsidising teleworking have significant effects on the dynamics of the epidemic and noticeably reduce its peak, the total number of infections and death rate. These policies also increase the profits of firms and their output. Subsidies to sick leave payments in firms can be counter-productive and increase infections because such policies reduce the willingness of firms to fight against infections. These subsidies increase the profits of firms but reduce output during the year when the epidemic started. On the contrary, increases in sick leave payments reduce infections and death. They also reduce profits, but increase output. In turn, policies eliminating payments to employees on leave reduce infections and death. These policies increase the profits of firms but substantially reduce their output in the year when the epidemic started.

We also simulate economic downturn assuming that it is proportional to the number of sick people and is caused by lockdown policies, production restrictions, and changes in the demand. During an economic downturn, firms fight against infections in the workplace less because the gains from having healthy workers are low. Firms anticipate the downturn and delay allocating employees to teleworking and allow them to get exposed to the disease at the beginning of the epidemic. The number of infections, the probability of catching the disease at the workplace, and death increase because of this. On the other hand, around the end of the downturn, firms have strong incentives to fight against infections because of the high probability of infections at the workplace as well as the anticipation of upturn, which increases the gains from this fight. At the end of the downturn, they choose to have a higher number of teleworking employees than in the benchmark, where there is no economic downturn. The profits and output also increase more with this fight than in the benchmark.

Taken together, our results imply that firms have incentives to fight against infections in the workplace and their choices of worker allocations into on-site work, teleworking, and leave have a significant effect on the dynamics of the epidemic. These choices significantly reduce the peak of the epidemic, the number of infections, and death. Policies, such as subsidies to teleworking and sick leave, can affect the choices of worker allocations in firms, the profitability of firms and their production, as well as the dynamics of the epidemic. Production restrictions, lockdowns and the resulting economic downturn also effect the choices of firms and the resulting dynamics of the epidemic.

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