Mass Casualty Treatment After Attacks on Critical Infrastructure: An Economic Perspective

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1 Introduction

Intentional attacks on critical infrastructure can cause mass casualties among civilians. Such attacks inflict economic loss in two different ways. First, such mass casualty incidents (MCIs) put significant strain on medical emergency services (MES) supply since such supply is not typically organized to consider extreme scenarios, implying resources for treatment are limited. Therefore, medical personnel must use triage to ration available supply and schedule treatment [1].

Second, as a consequence of the attack, a number of victims will not recover or remain permanently injured. In both cases, these victims represent an economic loss to the nation's labor force. As a result, the productivity of the economy suffers. Since the productivity of labor force participants differs according to whether they represent specialist, skilled, or unskilled labor, this loss is contingent on the number

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of victims in each group. Hence, intentional attacks on critical infrastructures may intend to disrupt economic productivity by targeting the labor force, such that persistent damage is inflicted. Since replacement time increases with labor force specialization, an MCI likely reduces labor productivity for a significant period of time [6].

Our analysis first draws up the event space of an MCI and then uses friction time analysis to model productivity loss. We then explore the effects of three different triage methods on economic loss reduction. In particular, we compare preferential to random treatment methods, investigating the extent to which these may reduce economic loss, if at the price of ethical dilemma.

2 The Consequences of Mass Casualty Incidents

Figure 1 draws up the event space after an MCI has occurred. A total number V of injured victims demands medical treatment. The limited medical emergency supply (MES) capacity M is deployed in order to treat as many victims as possible. If these victims are not treated within a particular timeframe, they cannot recover and hence these fulltime equivalents (FTEs) are lost $(V - M)$. If they receive treatment, a share $(\beta \cdot M)$ of victims under treatment does still not recover, and these FTEs are also lost. Another share $(\alpha \cdot M)$ recovers but suffers from permanently reduced health over their remaining lifespan (partial recovery). Some of these victims will never be able to return to the workforce, hence an additional number $(\alpha \cdot \gamma \cdot M)$ of FTEs is lost. The remaining victims, i.e. a share of $((1 - \alpha - \beta) \cdot M)$, fully recover. On the basis of this event space, our model explores the two major consequences of an MCI: First, the monetary loss to the economy as labor force participants must be replaced, and second, the strain such an event puts on medical supply capacity.

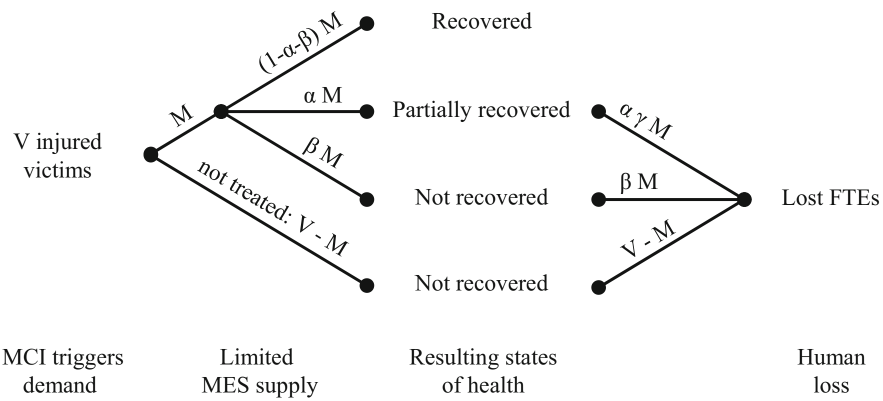

Fig. 1 Event space of victim treatment outcomes

Table 1 List of model parameters

Item	Parameter	Defined for
Population size	N	$\mathbb{N}^+$
Number of victims	V	$\mathbb{N}^+$
Number of groups with different average labor productivity	n	$\mathbb{N}^+ \in [0, V]$
Group number	i	$\mathbb{N}^+ \in [1, n]$
Group size (number of people in group i)	N_i	$\mathbb{N}^+$
Number of victims within group i	V_i	$\mathbb{N}^+ \in [0, V]$
Number of treated victims	M	$\mathbb{N}^+ \in [0, V]$
Lost full time equivalents	L	$\mathbb{R}^+ \in [0, V]$
Lost full time equivalents within group i	L_i	$\mathbb{R}^+ \in [0, N]$
Maximum duration of treatment	D	$\mathbb{N}^+$
Treatment duration	d	$\mathbb{N}^+, d < D$
Share of victims partially recovered after treatment	α	$\mathbb{R} \in [0, 1]$
Share of victims not recovered despite treatment	β	$\mathbb{R} \in [0, 1]$
Share of lost FTEs after partial recovery	γ	$\mathbb{R} \in [0, 1]$
Simplification parameter	η	$\mathbb{R} \in [0, 1]$
Average labor productivity of group i	h_i	$\mathbb{R}^+$
Lost labor productivity of all groups	H	$\mathbb{R}^+$
Lost labor productivity of group i	H_i	$\mathbb{R}^+ \in [0, H]$
Friction period to replace FTE in group i	T_i	$\mathbb{R}^+$
Friction period function type parameter	a	$\mathbb{R}^+, a > 0$
Friction period function parameter for scaling	c	$\mathbb{R}^+, c > 0$
Scaling factor of the sigmoid function	δ	$\mathbb{R}^+$
Total monetary loss	Π	$\mathbb{R}^+$
Monetary loss in group i	Π_i	$\mathbb{R}^+ \in [0, \Pi]$
Solow factor	ϵ	$\mathbb{R}^+, \epsilon > 1$
Lost labor productivity in all groups after Solow correction	H_ϵ	$\mathbb{R}^+, H_\epsilon \geq H$
Total monetary loss after Solow correction	Π_ϵ	$\mathbb{R}^+, \Pi_\epsilon \geq \Pi$

Table 1 provides an overview of all parameters used in our subsequent analysis of these two consequences.

2.1 Monetary Loss to the Economy

We assume that all victims, whether (if partially) recovered or not, were labor force participants. The total number of victims V can be subdivided into n groups that differ by their productivity levels h_i (for $i = 1 : n$ and with $h_1 > h_2 > \ldots > h_n$). The immediate loss of labor productivity over all n groups can be calculated as

$$H(t = 0) = \sum_{i=1}^{n} L_i \cdot h_i \tag{1}$$

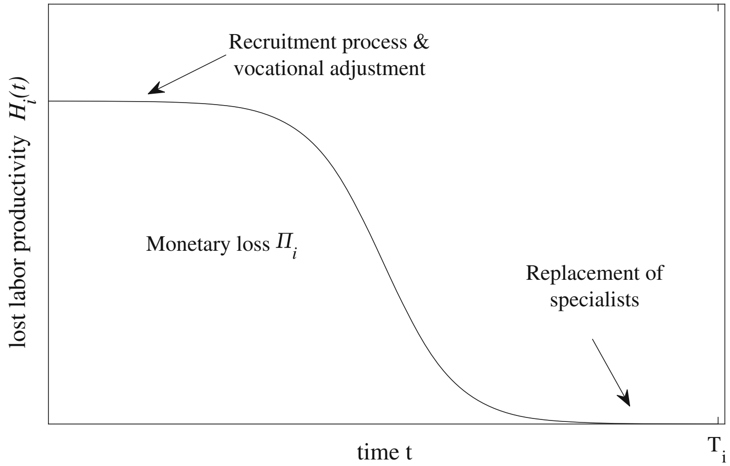

Fig. 2 Lost labor productivity $H_i(t)$ over time

where L_i reflects the lost full time equivalents in group i.

In principle, the impact of a loss of productive FTE for an economy could be modeled by considering the value of a statistical human life (e.g., [5, 9]). However, the reduction-in-loss estimates obtained by this method may be too high [6], and the replacement of large numbers of labor force participants requires significant time, both for the recruitment process and for vocational adjustment (friction time). In particular, specialists may be very hard to replace (if at all). We therefore prefer to use friction time analysis, proposing a scaled and shifted sigmoid function by which we can model the time-lagged replacement process [6, 10]. Figure 2 illustrates our approach.

As lost labor force participants are replaced, the loss of labor productivity in group i can be modeled as

$$H_i(t) = L_i \cdot h_i \cdot \left(1 - \underbrace{\frac{1}{1 + exp(\delta \cdot (1 - \frac{2t}{T_i}))}}_{\text{Scaled and shifted sigmoid function}}\right) \qquad t \in [0, T_i] \tag{2}$$

where T_i is the friction period and δ is a scaling factor that shapes the gradient of the curve. We shift and scale this function with $t' = \delta \cdot (2t/T_i - 1)$ such that $sigmoid(t') = 1/(1+exp(-t'))$ gives $f(t) = 1/(1+exp(\delta \cdot (1-2t/T_i)))$. Table 2 illustrates how this parameter shapes the share of FTEs replaced after a particular

Table 2 Share of FTEs replaced as a function of the sigmoid scaling factor δ

δ	3	4	4	6	7	8	9
$f(t = T_i)$ [%]	95.25	98.20	99.33	99.75	99.91	99.97	99.99

friction time has elapsed. As lost labor force participants are replaced, productivity loss decreases to zero as replacement time t converges to the friction period T_i.

T_i might differ among groups. Since replacing specialists probably takes much longer than replacing unskilled labor, friction time likely depends on both the number and the productivity of lost labor force participants that must be replaced. Hence, friction time can be specified as can be formulated as

$$T_i = c \cdot (L_i \cdot h_i)^a \tag{3}$$

where $a > 0$ and $c > 0$ are ancillary parameters that describe the capacity of the labor market to replace lost FTEs. The parameter c models the flexibility of the labor market. Larger values of c prolong friction time, for example in scenarios where the domestic labor market is unable to provide enough supply at short notice, or where bureaucratic or migration controls impede fast replacement of FTEs. The parameter a models the dependency type between the friction period and the lost labor productivity, such that $a = 1$ captures proportional and $a > 1$ disproportionate dependencies (e.g., when a severe epidemic wipes out many productive participants of the labor force). As these members are lost, the economy suffers a primary monetary loss due to lower labor productivity. The primary loss of group i can be calculated by integrating the lost labor productivity both over time, i.e. from the time the participants were lost ($t = 0$) until they were fully replaced ($t = T_i$), and over all groups

$$\Pi_i(T_i) = \int_0^{T_i} L_i \cdot h_i \cdot \left(1 - \frac{1}{1 + exp(\delta \cdot (1 - \frac{2t}{T_i}))}\right) dt = L_i \cdot h_i \cdot \frac{T_i}{2} \tag{4}$$

Integrating (3) into (4), the monetary loss in group i can be written as

$$\Pi_i = \frac{c}{2} \cdot (L_i \cdot h_i)^{a+1} \tag{5}$$

This loss is graphically represented in Fig. 2 by the area underneath the lost labor productivity curve $H_i(t)$.

Considering all groups, the overall labor productivity loss is

$$H(t) = \sum_{i=1}^{n} H_i(t) \qquad t \in [0, max(T_i)] \tag{6}$$

And thus the total primary monetary loss amounts to

$$\Pi = \sum_{i=1}^{n} \frac{c}{2} \cdot (L_i \cdot h_i)^{a+1} \tag{7}$$

However, in addition to this primary loss, there is also a secondary loss. Capital productivity also suffers as labor force participants are lost since machinery ceases to operate for a time or continues to be operated by less qualified staff (and hence at lower efficiency). Moreover, total factor productivity is reduced since lost labor force participants can no longer innovate. We consider this secondary loss by scaling primary loss with a group-specific ancillary parameter $\epsilon_i >= 1$, terming it Solow factor in honor of [8]. Total productivity and monetary losses are hence obtained after correcting (6) and (7) for such secondary loss:

$$H_\epsilon(t) = \sum_{i=1}^{n} H_i(t) \cdot \epsilon_i \qquad t \in [0, max(T_i)] \tag{8}$$

$$\Pi_\epsilon = \sum_{i=1}^{n} \frac{c}{2} \cdot \epsilon_i \cdot (L_i \cdot h_i)^{a+1} \tag{9}$$

2.2 Strained Medical Emergency Services Capacity

Supply for medical emergency services (MES) is limited, and hence only a limited number of victims can be treated within any given timeframe. This number M can be specified as a function

$$M = M(\frac{D}{d}, R) \tag{10}$$

where d is the treatment duration and D the time by which victims must have been treated to avoid certain death. Further, R comprises the available MES resources, i.e. personnel (doctors, nurses, etc.), infrastructure (hospitals, ambulances, etc.), and physical supplies (beds, equipment, drugs).

The event space we drew in Fig. 1 suggests that the total number L of lost labor force participants can be calculated as

$$\begin{aligned} L &= (V - M) + \beta \cdot M + \alpha \cdot \gamma \cdot M \\ &= V - M \cdot (1 - \beta - \alpha \cdot \gamma) \\ &= V - M \cdot \eta \end{aligned} \tag{11}$$

Note that the composite term $(1 - \beta - \alpha \cdot \gamma)$ is renamed to η to simplify the notation of the following equations. Stratifying L by groups yields

$$L_i = V_i - M_i \cdot \eta \tag{12}$$

where V_i is the number of victims in group i that require medical emergency service and M_i denotes the number of treated victims within group i. We now propose three methods to triage victims, and we explore the implications of each method for monetary loss. Thus, we analytically link human and economic loss, keeping medical supply constraints in mind. For all three methods, the number of victims treated in each group M_i is formally derived, then, using (12), the number of lost labor force participants can be calculated.

First In, First Out (FIFO) Triage methods such as START or SALT are typically recommended to optimize MES utilization [1, 2, 7]. Such concepts triage victims according to their level of injury and chances of survival. From an economic perspective, these treatments represent a random selection for which individual productivity is irrelevant; treatment is scheduled on a 'first come, first serve' basis.

Therefore, the number of victims randomly selected for treatment has a multivariate hypergeometric distribution [3], such that the number M_i of treated victims in each group i is

$$M_i = min(V_i, E[M_i]) = min(V_i, M \cdot \frac{V_i}{V}) \tag{13}$$

Preferential Treatment According to Productivity (PTAP) Treatment could also be rationed according to productivity levels. Under this scheme, victims belonging to the group with the highest labor productivity are treated first, those with the next highest are treated only if resources are still available, and so on until all resources are exhausted. The number of treated victims then is

$$M_i = min(V_i, max(0, M - \sum_{j=1}^{i-1} V_j)) \tag{14}$$

Minimization of Total Monetary Loss (MTML) A third triage option is to minimize total monetary loss to the economy, i.e. friction time is taken into account when scheduling treatment. Thus, the number of victims treated is obtained by using (12) in (9), which gives the optimization problem:

$$\min_{M_i} \sum_{i=1}^{n} \frac{c}{2} \cdot \epsilon_i \cdot ((V_i - M_i \cdot \eta) \cdot h_i)^{a+1} \tag{15}$$

Subject to:

$$\begin{aligned} &\sum_{i=1}^{n} M_i = M, \\ &M_i \in [0, V_i] \end{aligned} \tag{16}$$

The solution to this problem provides an optimal number of treatments M_i in each group i while minimizing total monetary loss Π_ϵ. This function is convex except for the cases of $a = 0$ and $a = 1$ which can be solved by Linear and Quadratic

Programming, respectively. Convex Programming is required to solve the problem for any a [4].

3 Illustration for Three Model Economies

We illustrate our concept by introducing the three model economies of Switzovenia, Tyrrhenia, and Aequatoria. These all differ in terms of population, labor productivity, and MES supply. While both Switzovenia and Tyrrhenia have small but highly productive populations, Aequatoria is a densely populated developing economy whose large unskilled labor force has low productivity. While MES supply is limited in both Aequatoria and Switzovenia, it is substantially larger in Tyrrhenia.

For each economy we simulate the impact of three distinct MCIs caused by deliberate attacks on critical infrastructures: A mass shooting in an underground network that causes 1000 victims, a series of bomb attacks on railway infrastructure that affects 10,000 victims, and an epidemic spread through intentionally contaminated drinking water that causes 100,000 victims.

3.1 Parametrization

The three model economies are specified by the parameters documented in Table 3. The population in each economy can be partitioned into ($n = 3$) groups (specialists, skilled labor, and unskilled labor) with different average productivity levels (h_1, h_2, h_3) with $h_1 > h_2 > h_3$.

Table 3 Specific parameters of model economies

Parameter	Switzovenia	Tyrrhenia	Aequatoria
Group size in millions $\{N_1, N_2, N_3\}$	{2, 2.5, 0.5}	{5, 12, 3}	{3, 10, 87}
Avg. labor prod. $\{h_1, h_2, h_3\}$ [$/h]	{100, 80, 55}	{100, 50, 30}	{85, 30, 8}
Solow factor $\{\epsilon_1, \epsilon_2, \epsilon_3\}$	{1.06, 1.05, 1.0}	{1.08, 1.04, 1.0}	{1.0, 1.0, 1.0}
Maximum number of treatments	5000	25000	500
Friction period parameter a	1	1	1
Friction period parameter c	0.007	0.0105	0.056
Scaling factor of the sigmoid function δ	5	5	5
Share of victims			
Partially recovered α	0.2	0.2	0.2
Not recovered β	0.1	0.1	0.1
Partially recovered but lost as FTEs γ	0.5	0.5	0.5

To simplify the computation, we set the ancillary parameter a to 1. Thus, the optimization problem can be solved by Quadratic Programming and noted in vector notation with $\mathbf{x} = [M_1, M_2, M_3]^\top$ and $\mathbf{v} = [V_1, V_2, V_3]^\top$ as

$$\min_{\mathbf{x}} = \frac{1}{2} \cdot \mathbf{x}^\top \cdot \mathbf{H} \cdot \mathbf{x} + \mathbf{f}^\top \cdot \mathbf{x} \tag{17}$$

Subject to:

$$\begin{aligned} \mathbf{A} \cdot \mathbf{x} &\leq b \\ \mathbf{0} \leq \mathbf{x} &\leq \mathbf{v} \end{aligned} \tag{18}$$

where

$$\mathbf{H} = c \cdot \eta^2 \cdot \begin{bmatrix} \epsilon_1 h_1^2 & 0 & 0 \\ 0 & \epsilon_2 h_2^2 & 0 \\ 0 & 0 & \epsilon_3 h_3^2 \end{bmatrix} \tag{19}$$

$$\mathbf{f} = -c \cdot \eta \cdot \begin{bmatrix} \epsilon_1 h_1^2 V_1 \\ \epsilon_2 h_2^2 V_2 \\ \epsilon_3 h_3^2 V_3 \end{bmatrix} \tag{20}$$

$$\mathbf{A} = \begin{bmatrix} 1 \cdots 1 \end{bmatrix} \tag{21}$$

$$b = M \tag{22}$$

For the case of Switzovenia, we set the ancillary parameter c such that such that the replacement of 1000 FTEs with an average labor productivity of $h_{avg} = h_2 = 80\$/\text{h}$ takes 3 months (=548 working hours):

$$c = \frac{T_{avg}}{L \cdot h_{avg}} = \frac{548\,\text{h}}{1000 \cdot 80\$/\text{h}} = 0.007 \tag{23}$$

We assume this baseline value is exceeded by 150% in Tyrrhenia and by 800% in Aequatoria due to greater transaction cost and labor market inflexibility. Thus, we obtain ($c = 150\% \cdot 0.007 = 0.0105$) and ($c = 8 \cdot 0.007 = 0.056$), respectively.

3.2 *Simulation Results*

Tables 4, 5 and 6 detail the simulation results for all model economies. Victims, treated victims and lost FTEs are in thousands, and total monetary loss Π_ϵ is in millions.

Table 4 Simulation results for Switzovenia

Switzovenia		FIFO	PTAP	MTML
Shooting				
Victims	$\{V_1, V_2, V_3\}$	0.4, 0.5, 0.1	0.4, 0.5, 0.1	0.4, 0.5, 0.1
Treated victims	$\{M_1, M_2, M_3\}$	0.4, 0.5, 0.1	0.4, 0.5, 0.1	0.4, 0.5, 0.1
Lost FTEs	$\{L_1, L_2, L_3\}$	0.08, 0.1, 0.02	0.08, 0.1, 0.02	0.08, 0.1, 0.02
Total monetary loss	Π_ϵ	0.477	0.477	0.477
Bombs				
Victims	$\{V_1, V_2, V_3\}$	4, 5, 1	4, 5, 1	4, 5, 1
Treated victims	$\{M_1, M_2, M_3\}$	2, 2.5, 0.5	4, 1, 0	2.6, 2.4, 0
Lost FTEs	$\{L_1, L_2, L_3\}$	2.4, 3, 0.6	0.8, 4.2, 1	1.9, 3.1, 1
Total monetary loss	Π_ϵ	429	449	370
Epidemic				
Victims	$\{V_1, V_2, V_3\}$	40, 50, 10	40, 50, 10	40, 50, 10
Treated victims	$\{M_1, M_2, M_3\}$	2, 2.5, 0.5	5, 0, 0	5, 0, 0
Lost FTEs	$\{L_1, L_2, L_3\}$	38.4, 48, 9.6	36, 50, 10	36, 50, 10
Total monetary loss	Π_ϵ	109,872	107,940	107,940

Table 5 Simulation results for Tyrrhenia

Tyrrhenia		FIFO	PTAP	MTML
Shooting				
Victims	$\{V_1, V_2, V_3\}$	0.25, 0.6, 0.15	0.25, 0.6, 0.15	0.25, 0.6, 0.15
Treated victims	$\{M_1, M_2, M_3\}$	0.25, 0.6, 0.15	0.25, 0.6, 0.15	0.25, 0.6, 0.15
Lost FTEs	$\{L_1, L_2, L_3\}$	0.05, 0.12, 0.03	0.05, 0.12, 0.03	0.05, 0.12, 0.03
Total monetary loss	Π_ϵ	0.3	0.3	0.3
Bombs				
Victims	$\{V_1, V_2, V_3\}$	2.5, 6, 1.5	2.5, 6, 1.5	2.5, 6, 1.5
Treated victims	$\{M_1, M_2, M_3\}$	2.5, 6, 1.5	2.5, 6, 1.5	2.5, 6, 1.5
Lost FTEs	$\{L_1, L_2, L_3\}$	0.5, 1.2, 0.3	0.5, 1.2, 0.3	0.5, 1.2, 0.3
Total monetary loss	Π_ϵ	34	34	34
Epidemic				
Victims	$\{V_1, V_2, V_3\}$	25, 60, 15	25, 60, 15	25, 60, 15
Treated victims	$\{M_1, M_2, M_3\}$	6.2, 15, 3.8	25, 0, 0	15.5, 9.5, 0
Lost FTEs	$\{L_1, L_2, L_3\}$	20, 48, 12	5, 60, 15	12.6, 52.4, 15
Total monetary loss	Π_ϵ	54,810	51,621	47,544

These results suggest that the consequences of intentional attack depend on both the number of victims and the configuration of the model economy. If not more than 1000 victims suffer from the attack, in terms of lost FTEs there is no difference between the three triage concepts in both Switzovenia and Tyrrhenia, and differences are small for the case of Aequatoria. Total monetary loss is largest in Aequatoria and is also influenced by the triage method applied there, whereas there is no such influence in Switzovenia or Tyrrhenia. However, this picture changes

Table 6 Simulation results for Aequatoria

Aequatoria		FIFO	PTAP	MTML
Shooting				
Victims	$\{V_1, V_2, V_3\}$	0.03, 0.1, 0.87	0.03, 0.1, 0.87	0.03, 0.1, 0.87
Treated victims	$\{M_1, M_2, M_3\}$	0.01, 0.05, 0.44	0.03, 0.1, 0.37	0.03, 0.08, 0.39
Lost FTEs	$\{L_1, L_2, L_3\}$	0.02, 0.06, 0.52	0.01, 0.02, 0.57	0.01, 0.04, 0.55
Total monetary loss	Π_ϵ	0.644	0.608	0.598
Bombs				
Victims	$\{V_1, V_2, V_3\}$	0.3, 1, 8.7	0.3, 1, 8.7	0.3, 1, 8.7
Treated victims	$\{M_1, M_2, M_3\}$	0.01, 0.05, 0.44	0.3, 0.2, 0	0.25, 0.25, 0
Lost FTEs	$\{L_1, L_2, L_3\}$	0.29, 0.96, 8.35	0.06, 0.84, 8.7	0.1, 0.8, 8.7
Total monetary loss	Π_ϵ	165	154.1	153.8
Epidemic				
Victims	$\{V_1, V_2, V_3\}$	3, 10, 87	3, 10, 87	3, 10, 87
Treated victims	$\{M_1, M_2, M_3\}$	0.01, 0.05, 0.44	0.5, 0, 0	0.5, 0, 0
Lost FTEs	$\{L_1, L_2, L_3\}$	3.0, 10, 86.7	2.6, 10, 87	2.6, 10, 87
Total monetary loss	Π_ϵ	17,761	17,451	17,451

once the number of victims grows. For a scenario of 10,000 victims, there is a significant influence of the triage method in all three economies. Compared to FIFO, the MTML method reduces total monetary loss by 13.8% in Switzovenia and 6.7% in Aequatoria, while there is no influence in Tyrrhenia. This is due to the much larger capacity for treatment in this economy; the system has enough slack to satisfy all demand for treatment. In the extreme case of an epidemic with 100,000 victims, monetary loss is largest in Switzovenia since many highly productive labor force participants cannot recover. Given the larger capacity for MES supply in Tyrrhenia, monetary loss is 50.1% lower for random and 56% for MTML triage, but the loss is still significant. The relative differences between the three triage concepts are also largest in Tyrrhenia, whereas there is only a minor influence of triage on total monetary loss in Switzovenia and Aequatoria.

3.3 Minimization of Monetary Loss

Figures 3, 4, and 5 show simulation results for all three economies when victims are triaged such as to minimize total monetary loss to the economy. In each figure, the thin vertical line to the left-hand side of the diagram represents the capacity limit M up to which all victims can be treated (Switzovenia: 5000; Tyrrhenia: 25,000; Aequatoria: 500). In all analyses, these capacities are held constant whereas the number of victims varies. The upper plot shows how many victims from each of the three population subgroups (specialists, skilled and unskilled labor) are treated if MTML triage as defined in formulae 15 and 16 is applied. The lower plot shows

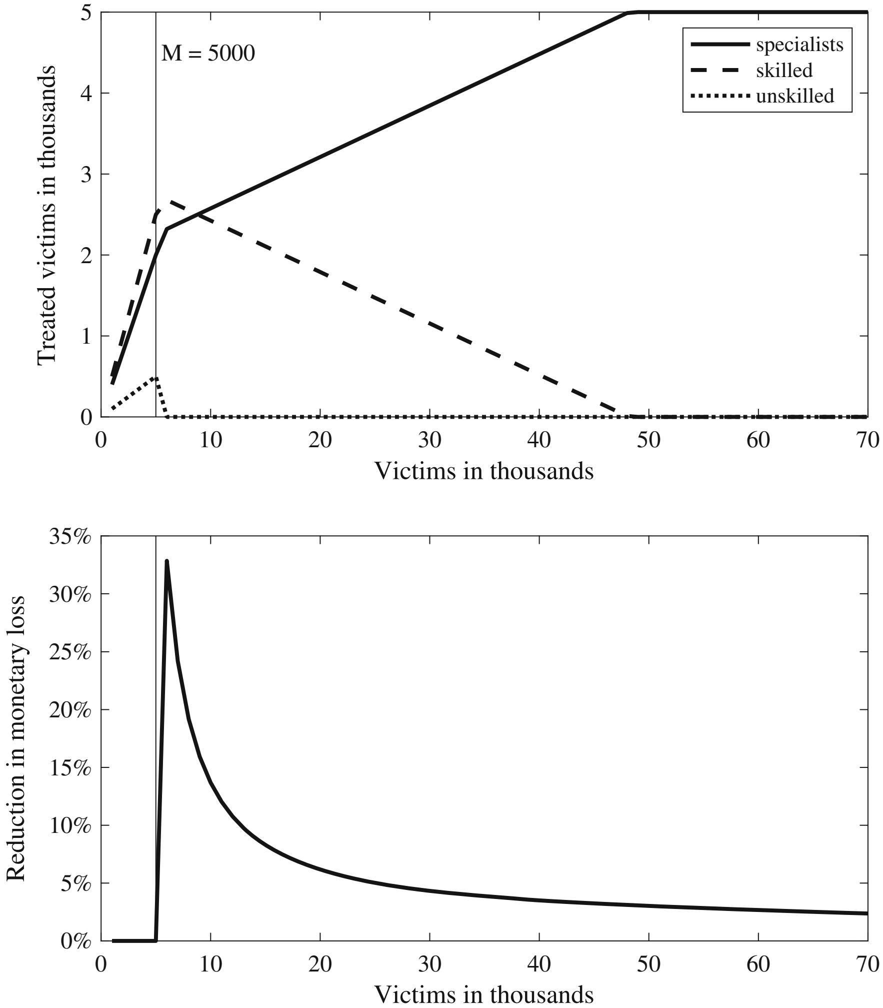

Fig. 3 Reduction of monetary loss in Switzovenia

the relative reduction of monetary loss which is calculated as the difference in loss between FIFO and MTML triage, i.e. $(\Pi_{\epsilon,FIFO} - \Pi_{\epsilon,MTML})/\Pi_{\epsilon,FIFO}$.

This relative difference is nil as long as the number of victims does not exceed MES supply; but if it does, then MTML triage reduces monetary loss by up to 32.8% in Switzovenia (48.4% in Tyrrhenia, 7.3% in Aequatoria). As the number of victims who seek treatment grows, the relative reduction of monetary loss converges to zero.

The analysis suggests that treatment scheduling is contingent on group membership once the number of victims exceeds MES supply in the respective economy. Whenever the number of victims V exceeds the capacity limit M, then MTML

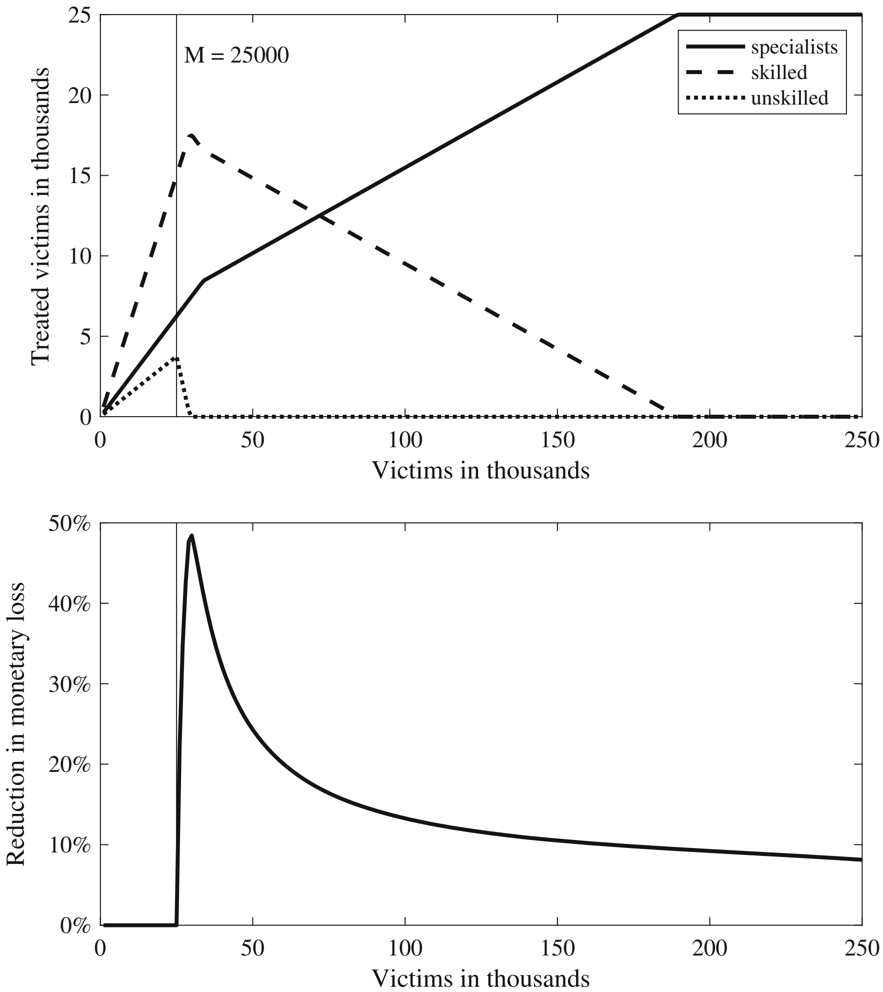

Fig. 4 Reduction of monetary loss in Tyrrhenia

triage suggests to first reduce treatment for unskilled labor (dotted lines in all figures), and then to reduce treatment for skilled labor (dashed lines). In other words, specialists receive preferential treatment, and treatment of the remaining labor force is rescheduled subject to remaining capacity. Should the number of victims in Switzovenia exceed 49,000 (in Tyrrhenia: 190,000; in Aequatoria: 22,800), MTML triage suggests to exclusively treat specialists.

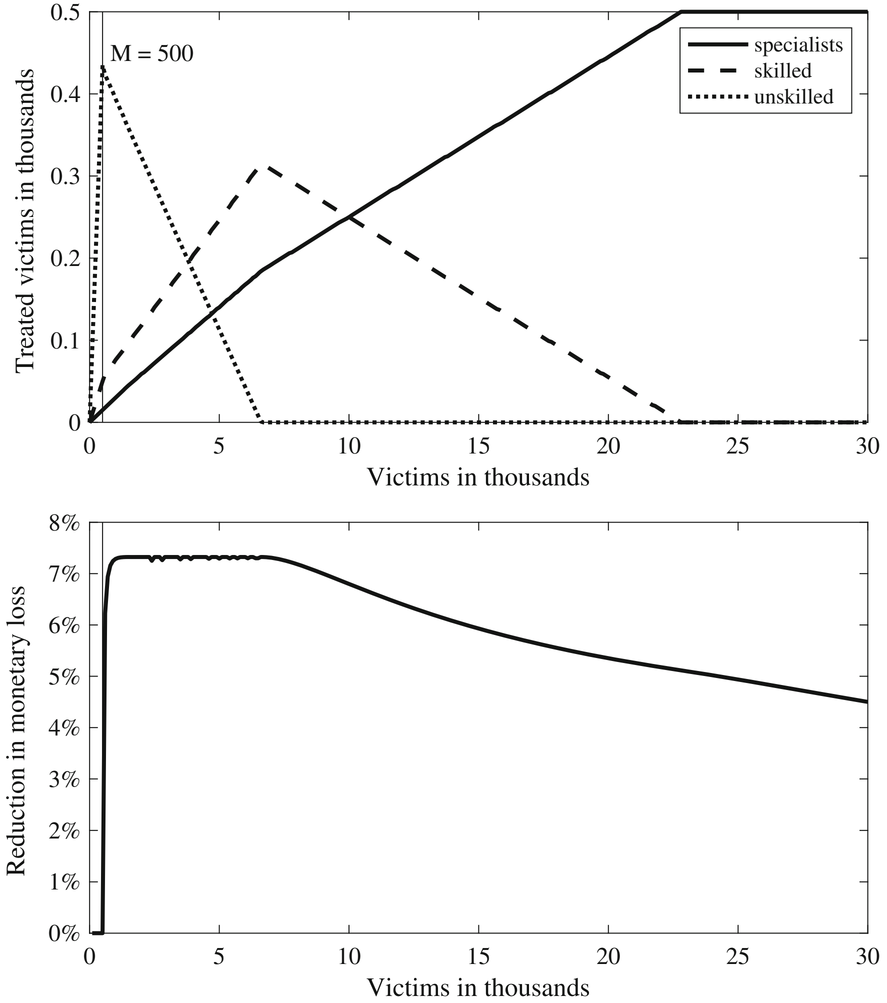

Fig. 5 Reduction of monetary loss in Aequatoria

4 Discussion

Our analysis suggests that whenever the number of victims inflicted by an MCI exceeds MES supply, a conflict between saving the economy from significant productivity loss and saving human lives exists. Using triage concepts such as our proposed MTML significantly reduces up to 48.4% of the monetary loss to the economy that is inflicted by an MCI. However, this triage also induces an ethical dilemma, since any preferential treatment on grounds of individual productivity is incompatible with the Hippocratic oath.

This dilemma can be somewhat mitigated if MES supply is increased by an additional emergency supply that can be made operational and scaled at short notice. However, such spare capacity would be expensive to build and maintain since it would barely be utilized in the absence of extreme events. Still, if the number of victims is very high, it will probably exceed any spare capacity. In this case, our MTML triage concept suggests that preferential treatment should be applied by treating the most productive members of the labor force first and then ration the remaining capacity among the less productive groups in order to maintain the productivity of the economy.

Without this minimization of friction time for specialists, the significant loss of labor force participants likely induces a productivity loss the neutralization of which will take a very long time. This perspective makes intentional attacks on critical infrastructure particularly dangerous, since the economic consequences of such an attack may change political majorities and society itself. It goes without saying that such extreme scenarios can only be imagined in the case of an uncontrolled epidemic, war, or massive terrorist attacks. Still, they illustrate the ethical dilemma any society would face under such circumstances. Hence, infrastructure defense is key to minimize the chance that such devastating attacks could ever occur.

The parametrization we provided is specific to the three model economies we conceptualized, but the simulation model is not. As the reduction of monetary loss is contingent on the number of victims, MES supply, group productivity levels, and friction time, we invite future research to feed data from real economies into our model, complementing our approach with additional illustrations. Further, our model could be refined by taking additional socioeconomic effects into account.

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