

# Chapter 9

## Modelling the Economic Impacts of Epidemics in Developing Countries Under Alternative Intervention Strategies



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**Abstract** Modern levels of global travel have intensified the risk of new infectious diseases becoming pandemics. Particularly at risk are developing countries whose health systems may be less well equipped to detect quickly and respond effectively to the importation of new infectious diseases. This chapter examines what might have been the economic consequences if the 2014 West African Ebola epidemic had been imported to a small Asia-Pacific country. Hypothetical outbreaks in two countries were modelled. The post-importation estimations were carried out with two linked models: a stochastic disease transmission (SEIR) model and a quarterly version of the multi-country GTAP model, GTAP-Q. The SEIR model provided daily estimates of the number of persons in various disease states. For each intervention strategy the stochastic disease model was run 500 times to obtain the probability distribution of disease outcomes. Typical daily country outcomes for both controlled and uncontrolled outbreaks under five alternative intervention strategies were converted to quarterly disease-state results, which in turn were used in the estimation of GTAP-Q shocks to country-specific health costs and labour productivity during the outbreak, and permanent reductions in each country's population and labour force due to mortality. Estimated behavioural consequences

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(severe reductions in international tourism and crowd avoidance) formed further shocks. The GTAP-Q simulations revealed very large economic costs for each country if they experienced an uncontrolled Ebola outbreak, and considerable economic costs for controlled outbreaks in Fiji due to the importance of the tourism sector to its economy. A major finding was that purely reactive strategies had virtually no effect on preventing uncontrolled outbreaks, but pre-emptive strategies substantially reduced the proportion of uncontrolled outbreaks, and in turn the economic and social costs.

**Keywords** CGE · Disease modelling · Ebola · Developing countries · Asia-Pacific

**JEL Classification:** C68, D58, I15, H51

## 9.1 Introduction

The Ebola outbreak which began in West Africa at the end of 2013 became by far the most severe Ebola epidemic to date. At the time we began the research reported in this chapter in late 2014, fears were held of exponential growth in infections in West Africa and the spread of the virus to other countries around the world. Fortunately, over the succeeding months the situation stabilised and by late 2015 the epidemic, which had cost over 11,300 lives, appeared over. As the Ebola emergency faded, there was an increasing focus on learning lessons from the outbreak in order to improve preparedness for any subsequent outbreak of Ebola, and of other emerging infectious diseases (EIDs) in general.

The research reported here was part of a 2014–15 study of the risks and consequences of Ebola spreading to certain developing countries in the Asia-Pacific region (McBryde et al. 2015). In this chapter, our concern is with the part of the study that examined the economic consequences that might have occurred if the disease had spread to two of these Asia-Pacific countries. Our estimations were carried out with two linked models: a stochastic disease transmission model and a multiregional dynamic computable general equilibrium (CGE) model of the world economy (a 9 industry, 15 region, quarterly version of the GTAP model, GTAP-Q). In this chapter, we report on simulations for two small countries, Fiji and Timor-Leste (East Timor).

Modelling the economic consequences of epidemics and pandemics forms an important component of preparing contingency plans for possible new outbreaks. In recent years there have been a number of such CGE studies, both with global CGE models (e.g. Lee and McKibbin 2004; Verikios et al. 2016) and national CGE models (e.g. Dixon et al. 2010; Verikios et al. 2012). Some of these CGE studies use historical disease data in developing the economic shocks in modelling actual outbreaks. In order to model on-going or hypothetical outbreaks, disease models are a good method for estimating the possible course of an outbreak. Verikios and his co-authors use versions of the long-established SIR epidemiological model to

estimate infection numbers for a hypothetical H1N1 epidemic in Australia (Verikios et al. 2012) and possible global influenza pandemics (Verikios et al. 2016).<sup>1</sup>

To date, CGE modelling of pandemics has primarily been of strains of influenza and viral respiratory diseases, such as SARS. Compared to these diseases, Ebola is characterised by a considerably longer delay between infection and symptom onset, an increasing degree of infectiousness as the disease progresses in the individual, a much longer period for an outbreak to reach epidemic proportions, and a much higher fatality rate (around 70% if untreated).

The difference in the time course of Ebola from those EIDs modelled to date raises a very different set of issues on response and intervention. Pandemic influenza outbreaks are much more likely to be self-limiting than a large Ebola outbreak, which in the absence of an effective response has the potential to cause larger scale, more damaging outbreaks.<sup>2</sup> Another difference relates to prophylactic behaviour. Crowd avoidance can decrease influenza transmission, but has a more limited effect in the case of Ebola for which there is no airborne transmission.<sup>3</sup> On the other hand, Ebola is transmitted by contact with blood or bodily fluids of an infected person, even after death (at which time the viral load is at its height). An effective Ebola transmission reduction response, therefore, includes a public education program informing of the dangers of cultural practices that involve long delays in burial and intimate contact with dead bodies.

In this chapter, we outline the approach taken to capture these distinctive features of an Ebola outbreak. This is reflected in the disease model developed for the study and the link with the CGE simulation. For a detailed discussion of the disease model, see Annex B of McBryde et al. (2015).

In Sect. 9.2.1, we describe the disease model; a stochastic SEIR-type model with additional compartments designed to capture essential features of Ebola transmission and proposed interventions. The model contains the key features of Ebola transmission described above, plus an explicit representation of the healthcare workforce capturing their varying exposure risks compared to the general population and their importance to impact control, the effects of local responses (e.g. hospital- and home-based isolation, tracing and monitoring of contacts and health capacity constraints), potential for interventions to assist early detection and case assessments, and behavioural modifications (e.g. safer burial practices).

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<sup>1</sup>The Susceptible-Infected-Removed (SIR) epidemiological model was first developed by Kermack and McKendrick (1927) and there have been many versions, usually involving more disease compartments over the past nine decades. SEIR models contain an extra compartment, E (Exposed).

<sup>2</sup>Influenza outbreaks (even pandemics) tend to be contained (at least in terms of greatest impact) to a single season, while the West African Ebola outbreak showed little indication of seasonality, and hence could have been anticipated to persist for a longer duration. Prior to its 2013–2015 West African outbreak, Ebola outbreaks had also been self-limiting, mostly due to their occurrence in very isolated rural regions of Africa.

<sup>3</sup>The portrayal in the media of Ebola as an unfamiliar and “horrific” disease may well mean that it has had greater impact on the public’s perception than influenza. It might thus be anticipated that there is a stronger behavioural response in respect to international tourism and trade.

An important feature of our disease modelling is that it is stochastic, rather than the deterministic modelling used in previous CGE exercises. This choice is driven by our stronger focus on the very early stages of a potential outbreak, and whether it is likely to occur or not, and what can be done to contain it at this stage, rather than assuming (as is more typical with influenza) that the outbreak will occur and then explore the effect of longer-term control strategies in containing the size of the outbreak.

These features of the disease model have implications for the CGE component of the modelling. The stochastic nature of the disease modelling allows probabilities to be put on the different CGE scenarios modelled. Also, the treatment of the relationship between behavioural responses and transmission probabilities allows aspects of the CGE modelling to be tied to disease modelling. For instance, costly crowd avoidance behaviour forms an important CGE shock, but due to its general ineffectiveness in transmission prevention, typical crowd avoidance behaviour does not impact on the disease model.

The structure and parameters of the SEIR model are based on published literature, including data stemming from the 2013–2015 West Africa outbreak and past outbreaks in Central Africa (e.g. Chowell and Nishiura 2014; The WHO Ebola Response Team 2014). Important aspects of the social and healthcare systems of the target countries were then incorporated using a combination of expert consensus, literature review and analysis of global datasets.

## 9.2 The Models

### 9.2.1 *The Disease Model*

#### 9.2.1.1 The Compartments

We start by describing our compartmental model of infection used to simulate the dynamics of an Ebola outbreak. We build this up in three stages, commencing with Stage 1, the basic model of compartments prior to detection of the disease, as depicted in Fig. 9.1. Here, since at the start of the 2013–2015 outbreak there was no available vaccine and limited potential for prior immunity, all individuals are initially classed as susceptible to infection (S). After infection, a person enters a latent incubation stage (E), from which they subsequently transition to an infectious, but not yet symptomatic, state ( $I^0$ ). At the time they develop symptoms (I), the person's infectiousness increases. Post-infection, individuals either recover with probability (1 minus the case fatality rate, CFR), and cease to be infectious (R), or die and remain infectious (D) until buried (B).

The outbreak is seeded with a single exposed individual, who we assume to be an active Ebola case who has travelled, undetected, from a region where Ebola is currently circulating. Susceptible individuals can then be infected by either

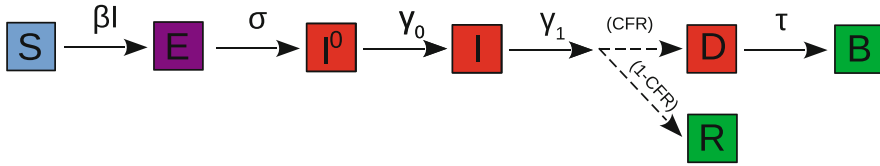


Fig. 9.1 Basic Ebola disease model

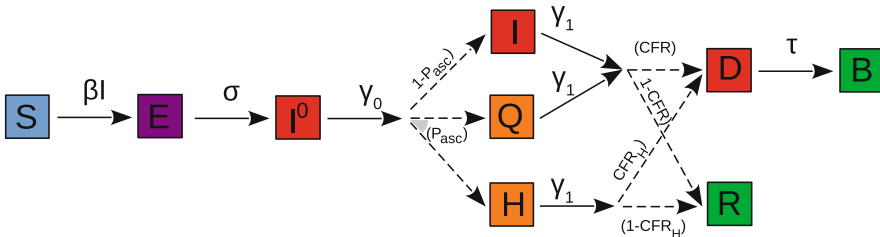


Fig. 9.2 Ebola disease model with isolation in a home (Q) and hospital (H) setting

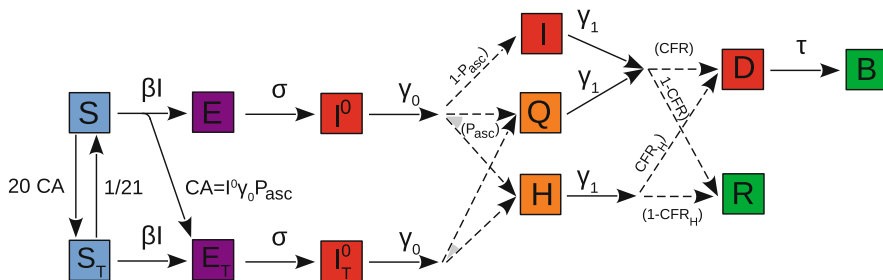
infectious and pre-symptomatic cases (at rate  $\beta_{I0}$ ), infectious and symptomatic cases (at rate  $\beta_I$ ) or dead but not yet buried individuals (at rate  $\beta_D$ ).<sup>4</sup>

In Fig. 9.2, we add two more compartments to represent the isolation of infectious cases in a hospital or home setting. Once Ebola is detected, future symptomatic cases are ascertained with probability  $P_{asc}$ , and subsequently isolated in hospital (H). The hospital-based isolation removes the risk of onward transmission to the general population, lowers the risk to healthcare workers and visitors, and increases the probability of survival ( $1 - CFR_H$ ).<sup>5</sup> Hospital beds/isolation wards are limited; and any cases ascertained while hospital-based isolation is at capacity are instead isolated in home quarantine (Q), which is assumed to reduce (but not remove) the risk of onward transmission, but not to affect the probability of recovery. Home quarantine is also limited, by a finite stockpile of personal protective equipment (PPE) and training capacity. Once this stockpile is exhausted, all future detected cases remain fully infectious and untreated in the community (I).

The full disease model is depicted in Fig. 9.3 where extra compartments are added to account for contact tracing and monitoring. In Fig. 9.3 monitored individuals are indicated by subscript T. Monitored individuals undergo a similar disease

<sup>4</sup>The parameters  $\sigma$ ,  $\gamma_0$ ,  $\gamma_1$  and  $\tau$  are the rates at which the exposed person becomes infectious, the rate at which the infectious person becomes symptomatic, and the rate at which symptomatic persons recover or die, and the rate at which a dead person is buried, respectively.

<sup>5</sup>In order to capture differences in exposure, the population is stratified into the general community and healthcare workers. Prior to detection the latter are at greater risk, but post-detection they are at a lower risk due to the adoption of stringent infection control measures. These risk differences are incorporated in separate  $\beta I$  parameters for the two groups. It is also assumed that if healthcare workers become depleted beyond a certain proportion all case ascertainment would cease and isolation of cases would no longer be possible.



**Fig. 9.3** Ebola disease model tracing and monitoring of contacts of ascertained cases

progression to the general community, but are always isolated if they become symptomatic, provided the healthcare capacity persists. For each ascertained case, 20 contacts are monitored for 3 weeks, subject to capacity constraints.

### 9.2.1.2 Interventions

We compare several types of intervention:

- (a) Improved surveillance, which may reduce the time to first Ebola detection, and/or increase the probability of ascertaining subsequent cases.
- (b) Increased isolation capacity (hospital-based and/or home quarantine/PPE), increasing the number of cases that can be isolated and/or traced and monitored.
- (c) Increased healthcare workforce, reducing the probability of depletion and collapse of the healthcare system.
- (d) Improved hospital facilities (disease treatment), reducing the case fatality ratio of hospitalised cases.
- (e) The introduction of safer burial practices, decreasing the delay between death and burial ( $\tau$ ) and/or reducing the rate of transmission per day from deceased cases.

We conduct alternative simulations based on the timing of these interventions: either deployed *pre-emptively*, prior to detection of the first Ebola case or *reactively*, at some point after first Ebola detection.

### 9.2.1.3 Patches

We model Ebola transmission and control in one or more *patches*, each corresponding to a single region within a country. We divide Timor-Leste and Fiji into two patches each—one urban, representing Dili and Suva respectively, and one rural, representing the remaining areas of each country. The numerical values of parameters differ between patches to capture regional differences in population

density (crowded living conditions in urban slums can increase transmission rates), quality of healthcare (size of healthcare workforce and number of hospital beds) and cultural differences (e.g. with burial practices). The patches are linked together by estimated daily people movement flows.

### 9.2.1.4 Simulation Outputs

The disease model is run stochastically to capture the distribution of possible outcomes arising from a small *initial* number of cases in a fashion that allows for the possibility that an outbreak would fail to occur, even in the absence of any response, simply due to initial cases recovering or dying without onward transmission. The model tracks the number of people in each disease compartment and is updated in discrete time steps of 1 day. At each time step, the number of people leaving each compartment is sampled from a Poisson distribution with a mean equal to the deterministic outflow rate for that compartment. Where there were multiple outflows from a compartment (e.g. from infectious (I) to dead (D) or recovered (R)), the number of people leaving was divided between the two destination compartments by sampling from a binomial distribution. Due to the stochastic nature of the model, each scenario was run 500 times to provide a probability distribution over possible outbreak sizes. We classify these outcomes into three broad categories:

- Stochastic fade out: Due to chance, insufficient people are infected for transmission to become established and the outbreak ends with fewer than 10–15 cases.
- Controlled outbreak: Transmission becomes established, but the local response and/or external intervention are able to limit the spread of infection and the outbreak ends with 100–500 cases (<0.1% of total population infected over 2.5 years).
- Uncontrolled outbreak: Transmission becomes established and grows to the point where the local response and an initial external intervention of the scale explored in this project are unable to prevent the continuing spread of infection, resulting in a substantial fraction of the population becoming infected during the outbreak.

As noted above, multiple realisations of the model were simulated for each scenario. For the purposes of CGE modelling, representative single realisations were selected from each of the Controlled and Uncontrolled Outbreak categories. These selections were made by choosing the realisation for which the final outbreak size was closest to the median final outbreak size for that category. Table 9.1 shows the proportions of simulations for each country by each intervention scenario that resulted in controlled outbreaks (first and third results column) and in uncontrolled outbreaks (second and fourth columns).

The results here are generated by multi-patch simulations. External interventions are of a pre-specified size, are triggered by detection of the outbreak, and are deployed in the capital; there is no adaptive response to outbreak conditions, and no “follow-up” interventions should control of the outbreak not be achieved. Beyond

**Table 9.1** Percentage of simulation runs resulting in controlled/uncontrolled outbreaks

	Fiji		Timor-Leste	
	Controlled	Uncontrolled	Controlled	Uncontrolled
Baseline	0	100	0	100
Reactive Small	0	100	0	100
Reactive Large	0	100	0	100
Pre-emptive Small	27.4	72.6	90.5	9.5
Pre-emptive Large	29.7	70.3	90.8	9.2

the change in burial practices, there is no adaptive change in population behaviour in response to outbreak conditions.

Table 9.1 excludes those simulations that resulted in stochastic fade-outs, which occurred in around 30% of cases. It can be seen that if the disease does not fade out that both reactive interventions, just as in the no-response baseline, result in uncontrolled outbreaks in 100% of cases. Only if interventions are pre-emptive are a proportion of outbreaks controlled.

## 9.2.2 *The Economic Model*

### 9.2.2.1 GTAP-Q

Given the quick rate at which global pandemics can spread, it is important that their economic effects are modelled dynamically with each period being considerably shorter than the annual basis upon which most dynamic CGE models are conducted. Consequently, Verikios et al. (2016) developed a quarterly version of the GTAP model (Hertel and Tsigas 1997; Ianchovichina and McDougall 2012), which we refer to here as GTAP-Q.<sup>6</sup> We use the theoretical structure of the GTAP-Q model for the present study of the economic impacts of Ebola.

The development of GTAP-Q required the introduction to the standard version of GTAP of two dynamic mechanisms. These relate to capital accumulation and labour market adjustment. The first of these ensures that a regional industry's capital stock at the start of a period is equal to its capital stock at the beginning of the previous period plus gross investment less depreciation during the previous period. Regional investment in a period is an increasing function of the region's expected rate of

<sup>6</sup>Quarterly models are particularly important when pandemics involve short and sharp peaks in their effects (see Verikios et al. 2016, p. 2). Thus, even an outbreak that is quickly contained might have a particularly disruptive effect for at least one quarter as a result of aversion behaviour. The consequent adjustment problem is likely to be missed if the impact on, say, tourism is averaged out over a year. Similarly, a rapid medical response to Ebola in a single quarter is likely to place considerably greater stress on the health system than a similar size response spread over the course of a year (a similar point was made by Dixon et al. (2010), with reference to an H1N1 outbreak).



return relative to the global rate of return. The second dynamic mechanism relates to the incorporation of a lagged wage adjustment process. In simulating the impact of an event, or policy change, a gap may open up between the demand and supply of labour in a region. The wage adjustment mechanism imposes sluggish movement in a region's wage rate such that it only slowly returns the regional labour market to equilibrium. Thus, short-run labour market responses to a shock (like Ebola) tend to be mainly expressed as changes in the unemployment rate (with little change in average wage rates from baseline), whereas long-run responses tend largely to be expressed as changes in average wage rates (with little change in unemployment rates from baseline). GTAP-Q is parameterised so that the deviation from baseline in excess labour demand or supply is eliminated in approximately 20 quarters.

Running simulations with a dynamic CGE model, like GTAP-Q, requires two simulations. The first simulation involves a baseline forecast driven by quarterly business-as-usual forecasts for certain variables with which the model is shocked.<sup>7</sup> The baseline simulation then computes the changes in all other variables consistent (in terms of the model's theory and database) with these outside forecasts. In the second simulation, normally referred to as the policy simulation, the model is run again with an *additional* set of shocks to reflect the particular policy, or event being analysed. The cumulative deviations between the results from the policy simulation and the baseline simulation thus represent the effects of the policy or event.<sup>8</sup> It is such deviations from baseline, which are reported below as the impact of the events (i.e. regional Ebola outbreak scenarios) modelled.

### 9.2.2.2 Adapting GTAP-Q for Modelling Asia-Pacific Developing Countries

The GTAP database allows flexibility with the countries and industries that are separately identified in the model. The GTAP-Version-9 database contains the required multi-regional input–output data for 140 regions and 57 sectors. The 140 regions comprise 121 individual counties, plus 19 regions, which each cover a group of countries. Neither of the two countries for which we model hypothetical Ebola outbreaks is included as a separate country in the 140-region GTAP database. Fiji is amongst the 23 countries that form the region “Rest of Oceania”, while Timor-Leste is included in “Rest of Southeast Asia” (along with Myanmar).

A major task, therefore, was to separate out these two countries (plus PNG, which was also modelled in the full study) from their respective regions. Only a limited amount of data is available for these countries, with the World Bank, UNSTATS

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<sup>7</sup>Where possible these are driven by macroeconomic and demographic forecasts from outside experts and trends in tastes and technology. For this study, the baseline forecast is driven by estimates for future quarterly movements in GDP and population for each of the model's regions.

<sup>8</sup>For the technical details on dynamic CGE policy analysis (such as the necessary changes to model closure between baseline and policy simulations), see Dixon and Rimmer (2002).

and the US Central Intelligence Agency being the major sources. Using this data, we employed estimation procedures developed by CoPS for splitting out countries from composite regions (i.e. from regions of more than one country) that generate the required multi-country input–output database (including international trade flows). For details of the procedures, see Horridge (2011).<sup>9</sup>

The outside data required to perform the regional disaggregation include:

- Value added, by industry, for Fiji, PNG and the remaining 21 countries in Rest of Oceania.
- Value added, by industry, for Timor-Leste and Myanmar in Rest of Southeast Asia.
- Value of international exports and imports by commodity for the countries within the two original composite regions.

As many of the 23 countries in the Rest of Oceania are very small, data for them are often not included in a single data source. Therefore, we have combined data from the following sources:

- UNSTATS: statistical databases from the United Nations Statistics Division. These include Commodity Trade Statistics Database (COMTRADE), and national accounts statistics on GDP and value added for industries at the one-digit level for both countries in Rest of Southeast Asia, and for 14 out of 23 countries in Rest of Oceania<sup>10</sup>.
- The CIA World Factbook and World Development Indicators, which contain GDP and three broad sectors (agriculture, industry and services) for almost all countries in the world.

These data are used by the SplitReg program to calculate the shares of all countries within each of the original composite regions (Horridge 2011). For each relevant composite region, the program then uses these shares to split the region's original GTAP input–output data into a region of focus and a residual region. This generates the required multi-regional input–output data for the composite region's new sub-regional structure.

The outcome was a GTAP-Q model comprising 15 regions, each containing 9 industries. The 15 regions consist of 6 separate countries (Australia, New Zealand, Fiji, Papua New Guinea, Timor-Leste and Indonesia) plus 9 multi-country regions (China and Hong Kong, Rest of Asia and Oceania, the United States and Canada, Rest of America, Europe, Middle East, West Africa, Rest of Africa and Rest of the World). The 9 industries are agriculture, fishing and forestry;

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<sup>9</sup>The procedures are carried out using the SplitReg program available from the Centre of Policy Studies archive at [www.copsmodels.com/archivep.htm#tpmh0105](http://www.copsmodels.com/archivep.htm#tpmh0105)

<sup>10</sup>The countries not covered by UNSTATS are American Samoa, Northern Mariana Islands, Pitcairn, Tokelau, United States Minor Outlying Islands and Wallis and Futuna.

mining; manufacturing; utilities; construction; trade; transport; other services; and government, education and health).<sup>11</sup>

### 9.2.3 *Linking the Models*

We conduct GTAP-Q simulations for the Ebola outbreak scenarios examined in the disease modelling for each of the four focus countries. From the disease modelling there are potentially 20 types of outbreaks, 10 for each country. These can be seen in Table 9.1 that shows for each country, and for each of 5 intervention scenarios, the proportions of outbreaks that result in small (controlled) outbreaks, and in large (uncontrolled) outbreaks. As noted in Sect. 9.2.1.3, for both Fiji and East Timor, baseline and reactive interventions result in 100% of outbreaks falling entirely into the uncontrolled outbreak category. This reduces the number of CGE simulations to be undertaken to 14.

For each outbreak scenario, we use as input to the economic modelling daily figures for disease prevalence by treatment and mortality for a representative outbreak event. This information from the disease modelling includes daily figures for prevalence, distributed among those persons hospitalised, those isolated in home quarantine and those fully infectious persons remaining in the community untreated.<sup>12</sup> It also included figures for the number of deaths and the number recovered on each day.

These figures were used to compute for each quarter, the number of hospital days and the number of days of home isolation. The daily figures were further disaggregated by persons of working age and non-working age. Applying participation and employment rates allowed the computation of working days lost each quarter due to illness—under the assumption that once a person becomes sick (infectious) they are (in non-fatal cases) either absent from work, or at work but largely unproductive, until 30 days after recovery.

## 9.3 The GTAP-Q Simulations

The disease model results discussed in Sect. 9.2.3 formed the basis on which to estimate the direct costs of each Ebola outbreak modelled: medical costs; reduced productivity through sickness, carer activities and quarantine; and a permanent reduction in a country's workforce through Ebola fatalities. We also use the information, particularly that of outbreak size, to estimate economic shocks

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<sup>11</sup>The model is kept to 15 regions in order to facilitate the analysis of the economic effects within the focus regions themselves, and the degree of spillover of economic effects to regions not experiencing the hypothetical outbreaks.

<sup>12</sup>That is, distributed into the categories H, Q and I as defined in Sect. 9.2.1.1.

resulting from behavioural effects that an outbreak is likely to induce.<sup>13</sup> Such shocks include aversion effects impacting on inbound and outbound (international) tourism, disruption to freight and passenger transport and a reduction in consumption associated with avoiding public places.

### 9.3.1 Increased Demand for Medical Services

The estimation of the quarterly medical costs of Ebola required the computation for each country of the daily costs of hospital-based isolation and treatment, of home-quarantine treatment, of case-tracing, Ebola testing, cleaning and burial costs.<sup>14</sup>

In order to estimate hospital costs in each focus country, we commence with daily hospital costs in each of the four countries, plus some comparison countries. These are shown in the first three columns of Table 9.2 for three categories of hospital. The daily hospital cost for treating Ebola cases in the United States is reported in the media to be between \$8000 and \$24,000. We assume a typical US hospital cost for Ebola of \$16,000 per day. We then estimated the daily hospital cost to treat Ebola in a focus country as equal to the daily US hospital cost for Ebola multiplied by the ratio of normal hospital costs in the country to normal hospital costs in the United States (shown in the last three columns of Table 9.2).

This method yielded the following hospital costs (in \$US):

	Per day	Per case
Fiji	\$919	\$5512
East Timor	\$82	\$494

Other medical costs were estimated as (1) Ebola tests—\$US 244 per test; (2) contact tracing—\$225 per infectious case and (3) burial and sanitation—\$404 per death. For home isolation cases, it is assumed the household is provided with a personal protection kit, and some elementary training in its use. The cost of the kit and training is assumed to be \$48 per case.

<sup>13</sup>The World Bank (2014) state that fear of contagion can cause both private persons and governments to undertake behaviours that disrupt trade, travel and commerce. They note that it is believed that such behavioral effects are believed to have been responsible for up to 80% or 90% of the economic effects of recent pandemics (SARS and H1N1), citing Lee and McKibbin (2004).

<sup>14</sup>At this stage, we do not include ambulance services as an extra cost, but rather assume that this is incorporated within hospital costs for Ebola cases.

**Table 9.2** Daily hospital costs

	Unit hospital cost estimates (\$), may include drug or lab costs			Ratio to the United States		
	Primary-level hospital	Secondary-level hospital	Teaching hospital	Primary-level hospital	Secondary-level hospital	Teaching hospital
Australia	1483.61	1547.76	2001.33	1.01	1.01	1.01
Fiji	84.64	88.30	114.18	0.06	0.06	0.06
PNG	21.12	22.03	28.48	0.01	0.01	0.01
Timor-Leste	7.59	7.92	10.24	0.01	0.01	0.01
Indonesia	43.67	45.56	58.91	0.03	0.03	0.03
United States	1474.12	1537.87	1988.53	1.00	1.00	1.00

Source: World Health Organisation

### 9.3.2 *Reductions in Productivity and Workforce*

It was assumed that one working day was lost for each day an employed person was symptomatic, and if they recovered for an additional 30-day period after that—representing the estimated time before they are fit to return to work. Following Verikios et al. (2011), these lost days are treated as reductions in labour productivity. That is, we assume that employers continue to make payments to Ebola-stricken persons by way of sick leave or incur other equivalent costs, and thus suffer an increase in their real unit (of output) labour costs during the lost days.<sup>15</sup>

We also assume that workdays are lost due to workers having to stay at home to care for Ebola patients, and to family members of Ebola patients having to undergo a period of home quarantine.

Little information on which to estimate lost-carers days was available. We made estimates using a Fijian example of patient employment status and household composition as a rough guide. Fiji is estimated by 2015 to have an average household size of 4.5, of whom on average 1.6 persons are employed (including in subsistence activities), 0.7 persons are engaged solely in home duties. 1.3 persons are under 15, a third of a person is over 14 and engaged in full-time study, and the remainder is unemployed, retired, etc. We consider separately Ebola patients who are employed and those not employed, and by whether they are hospitalised, quarantined at home, or are untreated and then estimate whether they require care, and/or quarantine, by household members who are employed. Clearly, there are many other factors that might affect the amount of carer leave taken, and our estimates should be considered very broad indeed. We estimated on this basis that on average a lost workday by an employed Ebola sufferer involved the loss of a further 0.4 workdays for a carer/quarantined person in treatment, or an additional 0.2 days for an untreated person.<sup>16</sup> For an Ebola patient (in treatment/quarantine) who was not in employment in the quarter, we estimate that for every sick day, an additional 0.7 days are lost. For non-employed untreated patients the additional lost days are half that. The reason for the greater number of lost days when the patient was not in work prior to becoming ill is that there are fewer available non-working family members to care for them (and a greater number of employed family members quarantined). When a patient died from Ebola, it was assumed that an additional 3 person-days were lost by grievers.

In the case of the death of persons of working age, we impose negative shocks to both the nation's population and its workforce size. In the case of Ebola-related fatalities of persons of non-working age a permanent reduction to population only is imposed.

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<sup>15</sup>This assumption is unlikely to be of any significance for the results reported in Sect. 9.4. It simply means that the cost of sick (and carer) leave is born entirely by owners of capital.

<sup>16</sup>The smaller workdays lost for an untreated patient is based on the assumption that this does not result in the quarantining of any other family members.

### ***9.3.3 Behavioural Effects 1: A Reduction in International Tourism***

A well-known effect of pandemics is its impact on international tourism (e.g. McKercher and Chon 2004). Verikios et al. (2011), citing Pine and McKercher (2004) and Wilder-Smith (2006), consider that regions undergoing a widespread influenza epidemic could incur reductions in inbound tourism in the range of 20%–70% during the peak infection period. Given the reports in the media regarding the reaction of international tourists (including government and airline travel restrictions) for the current West Africa Ebola outbreak, we assume that reductions in inbound tourism are likely to be at the high end of estimates reported in the literature. We assume, for both Fiji and Timor-Leste, a reduction of 50% in inbound tourism for a controlled outbreak, and an 80% reduction for an uncontrolled outbreak. These reductions are assumed to commence in the quarter that the outbreak is announced, moving to the full size of the assumed reduction by the next quarter. It is assumed for all countries that outbound tourism from the affected country falls in line with reductions in income. International tourism is assumed to begin to recover only after no new infections are observed in the affected country.

### ***9.3.4 Behavioural Effects 2: Crowd Avoidance***

Just as international tourists are likely not to visit countries with Ebola outbreaks, persons living in affected countries are likely to experience a significant fear of contagion. While, unlike international tourists, most residents must remain in the affected country, they are likely to avoid crowds where this is possible.<sup>17</sup> This necessarily means a reduction in expenditures that involve mixing in large crowds (e.g. large sporting and cultural events, markets and crowded retail precincts, public transport). Dixon et al. (2010) assume a 10% reduction in leisure purchases for a hypothetical H1N1 outbreak in the United States. Congressional Budget Office (2006) assumes a similar size reduction, but more concentrated; a 20% reduction in such purchases for one quarter.

Ebola outbreaks are likely to be longer lasting, and possibly generate more fear, than recent pandemics. In light of this, the above estimates may be considered a lower bound for the case of an Ebola outbreak. It is difficult, however, to ascertain the degree to which crowd avoidance for a United States pandemic might translate for developing countries analysed here. We modelled crowd avoidance for

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<sup>17</sup>Much of this type of behaviour can be considered sensible measures to avoid contagion. However, McKercher and Chon (2004) claim that in the case of SARS there was evidence that behavioural changes greatly exceeded this. Schulze and Wansink (2012) find that in that responses to perceived risk are more proportional where deliberation is possible, but disproportional for emotional or stressful situations.

uncontrolled outbreaks as though there were a 10% impost on purchasing outputs from service sector—that is, from Trade, Transport and Other Services. We include transport on the basis of the findings of Becker and Rubinstein (2011) that the “Al-Aqsa” Intifada terror attacks reduced bus tickets purchased by up to 9% in the subsequent week.<sup>18</sup>

### **9.3.5 Behavioural Effects 3: Increased Trade Costs**

Insufficient information was available to ascertain whether freight and port costs on merchandise trade to and from an infected country would be materially affected, or by how much. No effects of this type were modelled.

## **9.4 GTAP-Q Simulation Results**

In this section, we report simulation results for the effects of the 7 Ebola outbreak scenarios described in Table 9.1. We describe the economic effects of outbreaks in each country in turn, showing the time paths for the effects on GDP of the different outbreak scenarios in one figure and the time paths for the employment effects in a second figure. For each figure, the time paths are shown in terms of the percentage deviation from the baseline forecast for the variable (GDP or Employment) which results from the outbreak scenario.

### **9.4.1 A Fijian Outbreak**

Looking at Fig. 9.4 we see the time paths of the effects on GDP from the seven outbreak scenarios for Fiji. The time paths break into two identifiable groups: those for the two controlled outbreaks and those for the five uncontrolled outbreaks. Both controlled outbreaks involve pre-emptive action. The effects of both these scenarios follow an extremely similar time-path. The disease modelling showed a similar cumulative incidence over the four quarters of the outbreak for these scenarios, although there is some difference in their time path, with the prevalence more spread out (with more hospitalisation) under the slower/larger reactive intervention. However, the direct effects on GDP of the disease (increased medical costs, reduced productivity and reduced labour supply) are very small. It is the behavioural effects

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<sup>18</sup>A number of other behavioural reactions are not modelled. Examples include absenteeism from work as a crowd avoidance response, and lost days by parents needing to undertake child care as a result of school closures (as occurred in West Africa).



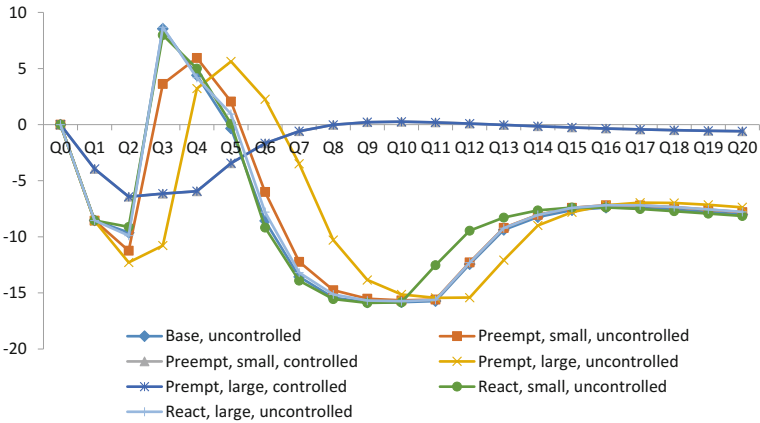


Fig. 9.4 Effects of different scenarios on Fiji’s real GDP (percentage deviation from baseline)

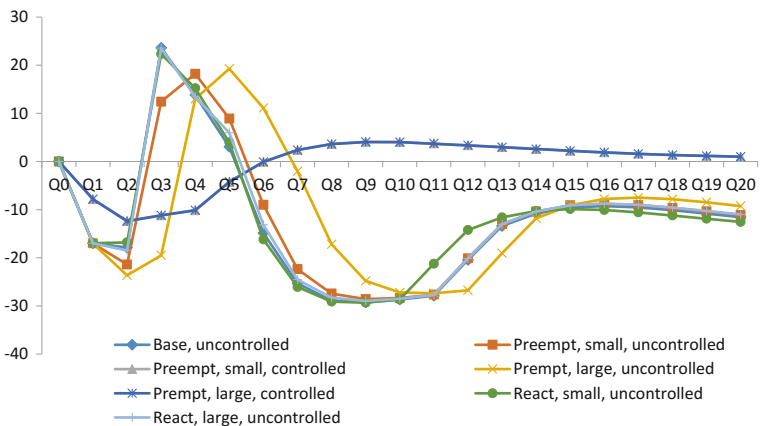


Fig. 9.5 Effects of different scenarios on Fiji’s employment (percentage deviation from baseline)

caused by the Ebola outbreak, which are responsible for nearly all of the GDP and employment impacts for these controlled outbreak scenarios. On the news of an Ebola outbreak in Fiji, it is assumed that international inbound tourism demand falls below baseline by almost 30% in the first quarter (Q1) of the outbreak; and by the second quarter (Q2) it is assumed that tourism demand falls further—to 50% below baseline demand (see Sect. 9.3.4). This results in GDP falling (relative to the baseline) by over 6% by Q2 for the two controlled outbreaks.

In Fig. 9.5, it can be seen that employment moves above baseline for 3 quarters from Q3 (or Q4 for the pre-emptive large outbreak) in the uncontrolled scenarios, and then from Q6 (or Q7 for the pre-emptive large outbreak) slowly move back towards baseline, and ultimately reaches a new equilibrium below baseline, over the remaining quarters of the simulation. The initial over-shooting of employment for

the 3 quarters is the result of interaction between the path for the wage rate and the path for the imposition and then attenuation of the direct economic consequences of the outbreak. Over the first two quarters in particular, as the direct effects of the outbreak are imposed on the Fijian economy, the real wage partly accommodates this by falling below baseline. Hence, when the direct effects of the outbreak attenuate over subsequent quarters, the real wage is temporarily below the level consistent with the return of the unemployment rate to baseline, leading to transitory employment overshooting.

Looking further at the uncontrolled outbreak cases, it can be seen that GDP and employment are negatively affected during the first two quarters of the outbreak due to adverse behavioural effects. For uncontrolled outbreaks, international tourism by Q2 is 80% below its baseline value, and the tourism sector represents around a quarter of the Fijian economy. By the third or fourth quarter, however, infections and their associated medical costs have risen enough to raise aggregate demand to a level sufficient to move GDP above baseline. The real wage (which moved below baseline with reduced tourism in the first two quarters) begins to adjust, however, to move resources towards the expanded medical sector. As medical expenditure peaks, increases in the real wage and negative movements in labour productivity put downward pressure on GDP and employment. By around Q10 GDP is about 16% below baseline for most uncontrolled outbreak scenarios, and employment around 29% below.

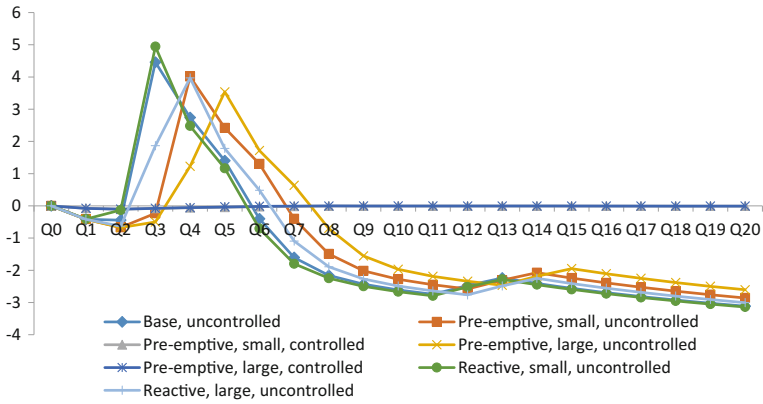
From Q11 to Q13, however, the end of the uncontrolled outbreaks sees international tourism demand commence its return towards baseline. This causes a smaller negative deviation in GDP over the remaining quarters of the simulation. By Q20, we see that employment is permanently below baseline, reflecting the reduction in the labour supply accompanying Ebola mortality.

### **9.4.2 A Timor-Leste Outbreak**

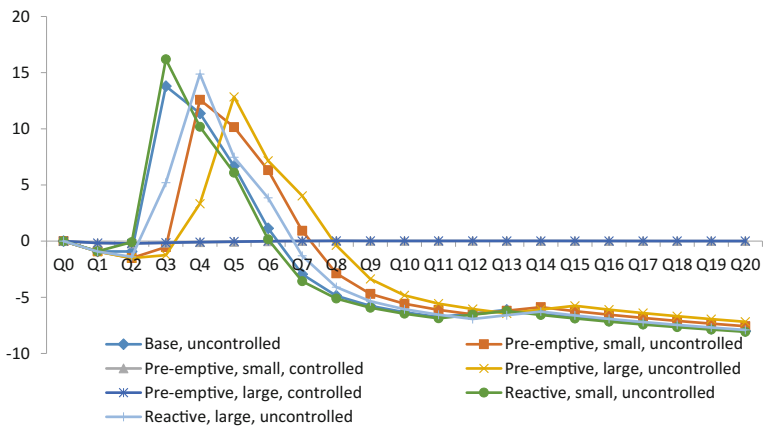
The effects of seven Ebola outbreak scenarios on Timor-Leste's GDP and employment are depicted in Figs. 9.6 and 9.7.

Unlike Fiji, controlled scenarios have only a small effect on the Timor-Leste economy. The direct impacts are small and Timor-Leste also has a relatively small tourism sector. Since crowd avoidance is not modelled for controlled scenarios, there is little by way of behavioural effects from the controlled outbreaks.

For the case of uncontrolled outbreaks, crowd avoidance causes a small reduction in aggregate demand in the first two to three quarters, before rising health costs results in a demand-induced increase in GDP in the next few quarters. After that, the labour market effects and the peaking of health expenditure results in increasing negative percentage deviations in GDP and employment from around Q6 to Q8 (depending on the time path of the direct effects of the uncontrolled outbreak). By Q20, GDP is about 3% below its baseline forecast value. This reflects the long-run



**Fig. 9.6** Effects of different scenarios on Timor-Leste's real GDP (percentage deviation from baseline)



**Fig. 9.7** Effects of different scenarios on East Timor's employment (percentage deviation from baseline)

fall in employment (about 6% relative to baseline) due to Ebola mortality reducing labour supply.

### 9.5 Concluding Remarks

In this chapter, we report the economic effects of hypothetical Ebola outbreak scenarios for two illustrative examples of developing countries in the Asia-Pacific region, Fiji and Timor-Leste. The simulations revealed very large economic costs associated with uncontrolled Ebola outbreaks, and in the case of Fiji, considerable

economic costs even for small outbreaks, due to that country's substantial reliance on international tourism.

The simulations were conducted over 20 quarters, with outbreaks commencing in the first quarter. While controlled outbreaks generally lasted only 3–5 quarters, and large outbreaks generally finished within 11–13 quarters, the economic effects were projected to last for a longer period. While the economy returned to close to its baseline forecast within the period modelled for those controlled outbreaks lasting only a few quarters, for uncontrolled outbreaks the economic effects extend beyond the 20 quarters of the simulations. For the large outbreaks, Ebola deaths reduced labour supply below baseline by as much as 18% by the end of the outbreak, but by Q20 there was insufficient time for labour–market adjustment to reduce employment by the same degree. Nevertheless, even for the period modelled, the economic impacts of large outbreaks on GDP and employment are large. For Fiji, the present value of the reduction in GDP over the 20 quarters is of the order of \$1.7 billion for the five large outbreak scenarios.<sup>19</sup> Furthermore, simulations were conducted under the assumption that affected countries borrowed to cover increased medical costs during the outbreak.<sup>20</sup> The present value of the increase in Fiji's external debt over the period is around \$1.1 billion to \$1.2 billion for the large outbreak scenarios.

The international tourism sector comprises about a quarter of Fiji's economy. A substantial portion of the cost for that country's economy is due to the contraction in this sector during the outbreak. Timor-Leste experiences large outbreaks infecting about the same proportion of its population as Fiji and has a population about one third larger than Fiji. However, with a much smaller tourism sector, Timor-Leste is projected to experience falls in GDP relative to baseline of the order of around \$0.7 billion to almost \$1.0 billion.

The direct effects of controlled outbreaks are small, and such outbreaks have only a negligible effect on the Timor-Leste economy, where the behavioural effects have limited impact. However, while the tourism reduction is smaller in Fiji for a controlled outbreak (50% rather than 80%), it still is sufficient to result in a negative impact on the nation's GDP for seven quarters; starting at almost 4% below baseline in Q1 before falling to almost 6% below baseline for the next three quarters, and then gradually returning to the baseline over the next three quarters. Since there are few deaths for controlled outbreaks, they cause little in the way of permanent effects on the Fijian economy. However, the temporary tourism reduction does have a negative impact on the country's trade balance for the period it lasts. The present value of Fiji's increased debt is just over \$0.3 billion.

The shocks for each CGE scenario were formed on the basis of simulation outputs of a stochastic disease model. This allows us to place probabilities on whether an outbreak is controlled or uncontrolled for each intervention scenario. Thus, assuming there is no stochastic fade out, all reactive interventions result in uncontrolled outbreaks. In the case of Fiji between 27% and 30% of small and

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<sup>19</sup>Dollar values are in USD.

<sup>20</sup>The reduction in Fiji's tourism exports also acts to increase the country's external debt.

large pre-emptive interventions, respectively, are estimated to result in controlled outbreaks, while for Timor-Leste pre-emptive interventions result in just over 90% of outbreaks being controlled. Thus, our linked disease-CGE model points to the importance of pre-emptive measures in improving the chances of reducing the substantial economic costs, as well as the human costs, of an uncontrolled Ebola outbreak if an infected person were to enter either of the illustrative countries examined.

It should be borne in mind, however, that while the economic and human costs for uncontrolled outbreaks are shown to be extremely high, these results should be viewed from the perspective that we assume no further response—either innate behaviour change by the population or additional external intervention—to escalating outbreak conditions. While such responses are likely, the range and complexity of potential effects require model development and parameterisation that are beyond the scope of this chapter.

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