

THE IMPORTANCE OF PERIODICITY IN MODELLING INFECTIOUS DISEASE OUTBREAKS

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Abstract

The economic effects of pandemic influenza, a regularly recurring form of infectious disease, are analysed. Epidemiological and economic models are linked to capture the transmission of the pandemic from regional populations to regional economies. The analysis builds on previous studies that apply computable general equilibrium (CGE) models with quarterly periodicity to assess the economic effects of infectious disease. The economic effects are assessed with the annual and quarterly periodicity, and the results are compared and contrasted. The analysis demonstrates the importance of quarterly periodicity as it can capture the short, sharp duration of influenza pandemics. The results demonstrate that annual economic models strongly underestimate the economic effects of infectious disease outbreaks that have a lifespan of less than one year because they can not accurately capture the time profile of the effects of an infectious disease outbreak.

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1. Introduction

Infectious diseases are a leading cause of death worldwide accounting for a quarter to a third of all mortality.¹ In most industrialised countries infectious disease ranks after cancer and heart disease as a leading cause of mortality. Despite developments in pharmaceuticals, infectious disease rates are rising due to changes in human behaviour, larger and denser cities, increased trade and travel, the inappropriate use of antibiotic drugs, and the emergence of new and resurgent pathogens (Dobson and Carper, 1996). Recent infectious disease outbreaks (i.e., HIV, H1N1, H5N1 and SARS) have demonstrated that infectious disease outbreaks can easily cross borders to threaten economic and regional stability (e.g., Chou *et al.*, 2004; Dixon *et al.*, 2010; Fan, 2003; Hai, *et al.* 2004; Lee and McKibbin, 2004; Verikios *et al.*, 2012). The threat to stability derives from a number of features of these outbreaks.

One, the nature of emerging diseases is that, by definition, they are not commonly encountered by physicians and are thus capable of generating widespread infection and mortality prior to identification of the etiologic agent (e.g., HIV/AIDS). Two, drug development and approval timeline lags well behind the emergence of these diseases such that the initial infection can result in significant mortality. Three, the constant adaptation of microbes, along with their ability to evolve and become resistant to antibacterial and antiviral agents, ensures that infectious diseases will continue to be an ever-present and ever-changing threat.

This work assesses the threats to regional economic stability from pandemic influenza, which is a regularly recurring form of infectious disease in history, with a focus on periodicity. There are a number of previous studies analysing on the economywide effects of global pandemics: some of these studies use macroeconomic (i.e., single sector) models; other studies apply a computable general equilibrium (CGE) (i.e., multi-sector) approach. A general equilibrium approach is the ideal framework for properly evaluating the economic impacts of public health emergencies such as pandemic influenza. A partial equilibrium approach that only focuses on the health sector and forgone incomes resulting from disease-related morbidity and mortality, while ignoring effects in other parts of the economy (e.g., Sander *et al.*, 2009), is inappropriate. Illness and death due to public health emergencies raises perceptions of risk, leading to risk-modifying behaviour (such as prophylactic absenteeism from work and public gatherings) in an effort to reduce the risk of contracting illness. Risk-modifying behaviour affects consumption and reduces labour productivity.

¹ See WHO (2004, p. 121, Annex Table 2) and WHO (2012).

Deaths due to illness reduce the availability of workers. Both of these effects will affect all parts of the economy to a greater or lesser extent.

An important feature of pandemics is their short, sharp nature; they usually begin and end within a year. Previous studies focusing on the economywide effects of global pandemics apply either a macroeconomic or CGE approach. Macroeconomic (i.e., single sector) approaches (e.g., Fan, 2003; Jonung and Roeger, 2006; Keogh-Brown *et al.*, 2010) have the advantage of applying quarterly models that allow them to capture the short, sharp nature of pandemics; they have the disadvantage of a single-sector approach that ignores sectors that are particularly relevant to the study of the economic effects of epidemics (e.g., medical services, inbound and outbound tourism). In particular, ignoring the tourism trade linkages across regions is a severe limitation in modelling a global infectious disease pandemic. CGE (i.e., multi-sector) approaches (i.e., Lee and McKibbin, 2004; Chou *et al.*, 2004; McKibbin and Sidorenko, 2006) apply models that have the advantage of identifying multiple sectors in the economy; they have the disadvantage of annual periodicity and so are unable to capture accurately the short, sharp nature of influenza pandemics.

The disadvantage of the CGE approach has been addressed by studies applying CGE models with quarterly periodicity, i.e., Dixon *et al.* (2010), Verikios *et al.* (2012) and Verikios *et al.* (2016). Building on these studies, a CGE model is applied that incorporates *variable* periodicity (i.e., quarterly and annual) to assess the global and regional economic effects of pandemic influenza. A major objective of this work is to demonstrate the importance of quarterly periodicity in assessing the economic effects of infectious disease outbreaks like pandemic influenza. Annual periodicity is inappropriate in simulating pandemics as it will smooth out short-term effects leading to potential underestimation of disruption. The inappropriateness of an annual model is demonstrated by modelling the economic effects of a given influenza pandemic using a model with both quarterly and annual periodicity. The results clearly show that assuming annual periodicity strongly understates the overall peak economic effects of an influenza outbreak. The development of quarterly periodicity from annual periodicity in the economic model applied here is formally presented. The results demonstrate that annual economic models have no place in economic analysis of infectious disease outbreaks that have a lifespan of less than one year.

2. The nature of influenza pandemics²

2.1 Overview

Influenza mortality, which can be highly variable from year to year, is a contributor to the variability in the annual mortality rate of industrialised countries. Influenza is a contagious disease and most often affects the upper airway and lungs of birds and some mammals. It causes seasonal epidemics globally and is a leading cause of infectious disease-related deaths in most countries. In non-pandemic years, influenza typically kills hundreds of thousands of people worldwide. The highest rates of mortality are in the elderly, followed by infants and children. Occasionally, influenza rates can reach pandemic proportions across the global population. There have been four influenza pandemics since the beginning of the 20th century—1918, 1957, 1968 and 2009—each of which was the result of a major genetic change to the virus.

Past influenza pandemics were characterised by the circulation through the population of a novel virus in non-seasonal patterns causing excess morbidity. The most severe of these was the 1918 Spanish Flu pandemic, where influenza mortality reached as high as thirty-five times the yearly average. More recently, May 2009 saw the emergence from Mexico of a new H1N1 virus capable of human-to-human transmission. The 2009 H1N1 virus was a novel type of influenza A, known commonly as ‘swine flu’ due to its close association with North American and Eurasian pig influenza. Highly transmissible, yet ultimately mild, it rapidly spread around the world, infecting 74 different countries in all six continents within five weeks. The rate of spread of the pandemic was far more rapid than previously observed and was enabled by high volumes of international air traffic. The WHO declared a pandemic on June 11, 2009. Thus, the virus took less than two months to emerge from Mexico and travel to all parts of the globe. It ultimately reached more than 200 countries and infected hundreds of millions of people. The WHO declared the pandemic over by the end of the year reflecting the brief lifespan of such viruses. In June 2010 the WHO reported over 18,000 confirmed fatalities from H1N1.

2.2 The effect on human behaviour

Direct economic effects of illness resulting from influenza include increased healthcare expenditures by patients and funders, and increased workloads for healthcare workers. Indirect effects include a permanently smaller labour supply due to deaths, and increased

² This section draws on Verikios *et al.* (2016), Section 2.

absenteeism from work by sick workers and by workers wishing to reduce the risk of contracting illness in the workplace, i.e., prophylactic absenteeism.

Prophylactic absenteeism is one example of voluntary risk-modifying behaviour in response to a pandemic. Other examples are reduced domestic and international travel, and reduced public gatherings at sporting and other events (Congressional Budget Office, 2006). Non-voluntary risk-modifying behaviour may be imposed on workers with children by school closures intended to mitigate the spread of the virus (Beutels *et al.*, 2008). Thus, some workers will be forced to take leave to care for young children. Workers who take paid leave from work, whether forced or voluntary, reduce their firm's labour productivity (i.e., output per worker) unless other workers can fully replace output lost due to absenteeism. This may be difficult during an influenza pandemic because the virus will be widespread and while many workers may not present to the health system, they are likely to be less productive than would otherwise be the case.

It is unclear what attitudes firms have towards absenteeism during pandemics, including whether they prepare for such events or whether it affects their hiring behaviour. A related question is whether firms utilise workers differently during pandemics, e.g., do they expect present workers to work harder or longer to compensate for output lost due to absent workers? And do pandemics directly impact investment behaviour by firms?

Fan (2003) argues that a pandemic will reduce business investment due to increased uncertainty and risk, leading to excess capacity. Similarly, consumer confidence will decline due to uncertainty and fear, leading to reduced spending as people elect to be homebound to reduce the probability of infection—this is another example of risk-modifying behaviour. Reduced consumer confidence may particularly affect services involving face-to-face contact (e.g., tourism, transportation and retail spending). James and Sargent (2006) argue that evidence from past pandemics suggests that it is mainly discretionary spending (e.g., tourism and transportation) that is reduced.

Fan (2003) also argues that an epidemic does not need to be of high morbidity and mortality in order to exert a large psychological impact on attitudes to risk. e.g., the 2003 SARS epidemic. James and Sargent (2006) evaluate this argument by examining evidence from the SARS epidemic and agree that people did experience increased fear of infection. Nevertheless, they argue that the evidence indicates that the only economic impact during the SARS epidemic was on air travel to affected locations and related impacts on accommodation. Keogh-Brown and Smith (2008) perform a retrospective analysis of the economic impact of the 2003 SARS epidemic and find that the economic effects were mainly

but not exclusively centred on East Asian regions, and that the effects went beyond air travel and accommodation.

3. The economic model

To model the economic consequences of pandemic influenza a modified version of the GTAP model is applied (Hertel and Tsigas, 1997). Below, the original model is initially described and then the modifications made thereto are formally presented.

3.1 The GTAP model

3.1.1 Implementation and solution

GTAP is a multi-regional, comparative-static, CGE model of world trade and investment that represents markets as perfectly competitive, industry technologies as linearly homogeneous, and traded goods as imperfectly substitutable. Formally, GTAP is represented by equations specifying behavioural and definitional relationships. There are m such relationships involving a total of p variables and these can be compactly written in matrix form as

$$A\mathbf{v} = \mathbf{0}, \quad (1)$$

where A is an $m \times p$ matrix of coefficients, $\mathbf{v}$ is a $p \times 1$ vector of percentage changes (or changes) in model variables and $\mathbf{0}$ is the $m \times 1$ null vector. Of the p variables, e are exogenous. Typically, the e variables describe changes in economic structure and policy (e.g., tariff rates, technology, etc). The e variables can be used to shock the model to simulate changes in the $(p - e)$ endogenous variables. Many of the functions underlying (1) are highly nonlinear, so writing the equation system like (1) allows us to avoid finding the explicit forms for these nonlinear functions. Thus, it is possible to write percentage changes in the $(p - e)$ variables as linear functions of the percentage changes in the e variables; this aids in computational efficiency. To do this, (1) is rearranged as

$$A_n \mathbf{n} + A_x \mathbf{x} = \mathbf{0},$$

where $\mathbf{n}$ and $\mathbf{x}$ are vectors of percentage changes in endogenous and exogenous variables. A_n and A_x are matrices formed by selecting columns of A corresponding to $\mathbf{n}$ and $\mathbf{x}$. If A_n is square and nonsingular, the percentage changes in the endogenous variables can be computed as

$$\mathbf{n} = -A_n^{-1} A_x \mathbf{x}. \quad (2)$$

Computing solutions to an economic model using (2) and assuming the coefficients of the A matrices are constant is the method pioneered by Johansen (1960).

Equations (1) represent the percentage-change forms of the nonlinear functions underlying the model; these forms are derived by total differentiation. Thus, (1) is an approximation based on marginal changes in the independent variables. So (2) only provides an approximate solution to the endogenous variables $\mathbf{n}$; for marginal changes in $\mathbf{x}$ the approximation is accurate but for discrete changes in $\mathbf{x}$ the approximation will be inaccurate. The problem of accurately calculating $\mathbf{n}$ for large changes in $\mathbf{x}$ is equivalent to allowing the coefficients of the A matrices to be nonconstant. The problem is solved by breaking the change in $\mathbf{x}$ into i equal changes. The multistep solution procedure requires that there are $(i-1)$ intermediate values of the underlying (levels) values of $\mathbf{n}$, i.e., $\mathbf{N}$. The intermediate values of $\mathbf{N}$ are obtained by successively updating the values of $\mathbf{N}$ after each of the i steps is applied. Once the values of $\mathbf{N}$ are updated for any given step, the coefficients of the A matrices in (2) are recomputed before (2) is solved again.

3.1.2 Intratemporal theory

This section presents the GTAP theory that describes how model variables relate to each other *within* a period,³ i.e., intratemporal theory. The theory of comparative-static models is mainly of intratemporal form and the GTAP model is the same as other comparative-static models in this respect. The intratemporal theory of GTAP is mostly retained for use in the dynamic model developed in Section 3.2.

GTAP represents the world economy by modelling economic activity occurring within and across regional economies. A regional economy may be either a single country (e.g., Australia) or a composite region consisting of many countries (e.g., the European Union). Each region produces a distinct variety of each commodity, which is imperfectly substitutable with the varieties produced by other regions. Within each region, each commodity is produced by a single-product industry from inputs of domestically-produced and imported commodities and five primary factors: skilled and unskilled labour, capital, land and natural resources (see Figure 1).

³ The time period in a comparative-static is amorphous and variable: amorphous because “Its...variables...all refer implicitly to the economy at some future time period.” (Horridge et al., 1993, p. 73), and variable because how far into the future they refer to depends on the nature of the model closure adopted, i.e., the list of exogenous and endogenous variables (Horridge *et al.*, 1993, p. 73).

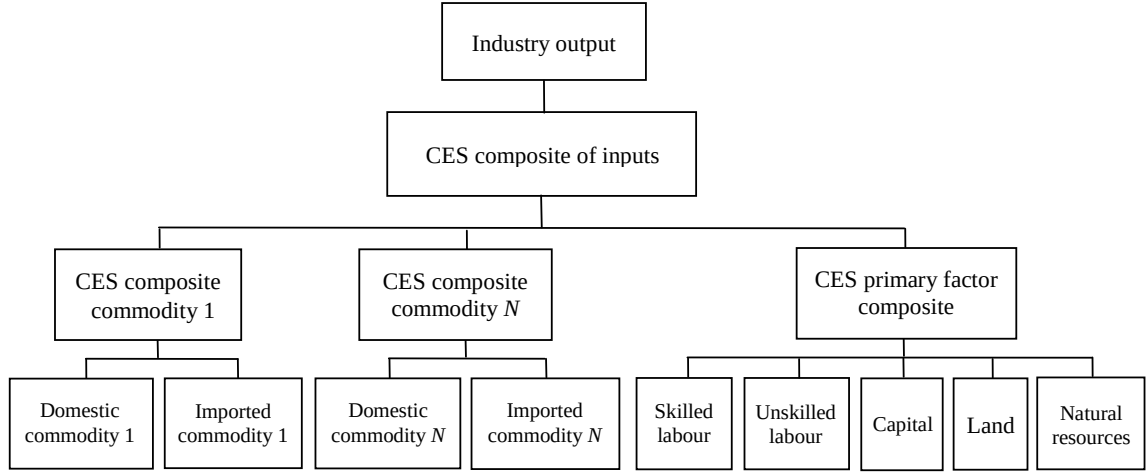


Figure 1. Structure of industry production technology in GTAP

Each primary factor is supplied to industries from a fixed regional endowment. The individual supplies of skilled and unskilled labour and capital are perfectly transformable across industries within a region, while land and natural resources are fixed in supply and industry usage. Consequently, wages for each labour type and the user price of capital are uniform across industries, but the rental prices of land and natural resources can vary across industries. Primary factor payments are subject to income taxes.

Commodities produced in each region are used as intermediate inputs in production, or consumed as inputs to final demand. There are four categories of final demand: investment, government consumption, household consumption and exports. Exports aside, final demands use composite commodities that are constant elasticity of substitution (CES) combinations of the domestic and the imported variety of each commodity, similar to composite commodity inputs for industries (Figure 1). Composite commodity inputs to investment and government consumption are determined by the application of CES production and utility functions, while a constant-differences-elasticity utility function is applied for household consumption.

Aggregate government and household consumption are determined by the allocation of regional income across government consumption, household consumption and saving to maximise a Cobb-Douglas utility function with variable scale and share parameters. Therefore, government and household consumption, and saving are almost fixed shares of regional income. Regional income equals primary factor returns plus net tax revenues.

Exports fall into two categories: commodities that are sold to other regions, and sales to an international pool of freight and insurance services that is used to convey internationally-traded commodities from source to destination regions. The international pool is a Cobb-

Douglas aggregate of the contributions from all industries in all regions. Only service sectors (e.g., transport and insurance) produce outputs that can contribute to this pool.

Total regional imports of each commodity are a CES composite of imports of the commodity from each exporting region. The prices determining the allocation of imports amongst exporting regions is the domestic price in the exporting region, plus net export taxes, plus per unit international freight and insurance costs, plus import tariffs. Thus the choice among sources of imports occurs at the economywide level, while the choice between the domestic and the imported (aggregated across sources) varieties of each commodity is made at the agent level.

3.2 Annual and quarterly dynamics

The GTAP model's major advantage as a tool for estimating the economic effects of influenza pandemics is its excellent regional and industry detail. But to accurately capture the dynamic behaviour of an infectious disease outbreak requires an economic model that is also dynamic. Further, the model must be able to capture the short, sharp duration of influenza outbreaks; this is the nature of past pandemics and the pandemic analysed here. Thus, GTAP is modified by incorporating dynamic mechanisms with *variable* periodicity: both annual and quarterly.

Dynamic CGE models with annual periodicity are common,⁴ whereas dynamic CGE models with quarterly periodicity are uncommon. Quarterly modelling within a macroeconomic (one sector) general equilibrium framework seems to begin with Kydland and Prescott (1982); this work started the real business cycle (RBC) literature. Quarterly modelling within a RBC framework with real or non-stylised sectors seems to begin with Hornstein and Praschnik (1994); they identify durable and nondurable goods sectors. Horvath (1998) develops a quarterly RBC model that uses the full spectrum of detail available in the US input-output tables. Kouparitsas (1998) develops a global quarterly model that combines aspects of the RBC and CGE traditions; it identifies five sectors. Adams *et al.* (2001) develop a quarterly CGE model of Australia that identifies 21 sectors.

Annual models are well suited to analysing events that last for about a year or more. For events that have short (less than a year) and sharp effects, a model with quarterly periodicity is more appropriate. An annual model is inappropriate here as it will smooth short-term effects leading to potential underestimation of disruption. For example, if a

⁴ Some recent examples include Böhringer and Welsch (2004), Dellink *et al.* (2004), Dixon and Rimmer (2002), Jorgenson *et al.* (2009), and Radulescu and Stimmelmayer (2010).

pandemic caused an 80% loss of inbound international tourism within a particular quarter, then the adjustment path of the tourism industry would be quite different from that in a situation in which international tourism declined by 20% for a year. Section 5 demonstrates this point by presenting the different adjustment paths for annual and quarterly models modelling an outbreak of pandemic influenza.

Annual CGE models are commonly solved in a recursive manner. The exceptions are intertemporal models that compute results simultaneously for all time periods, e.g., McKibbin and Wilcoxon (1999) and Malakellis (2000). Dynamic-recursive models usually divide time into discrete intervals and economic variables are assumed to change at the end of each interval.⁵ Such models take the form

$$\mathbf{Y} = G_i(\mathbf{X}), \quad (3)$$

where $\mathbf{Y}$ and $\mathbf{X}$ are vectors of endogenous and exogenous variables in a period, and $G_i (i=1,...,m)$ are m differentiable and continuous functions. Computations are then carried out according to

$$\Delta \mathbf{Y} = \nabla G_i(\mathbf{X}) \Delta \mathbf{X}, \quad (4)$$

where Δ refers to changes from one period to the next and $\nabla G_i (i=1,...,m)$ is a vector of first-order partial derivatives of G_i .

In (4), $\Delta \mathbf{X}$ represents changes from one year to the next for the exogenous variables. So to model quarterly changes it is necessary to divide $\Delta \mathbf{X}$ by four. To move from annual to quarterly periodicity it is also necessary to add equations that handle quarterly accumulation of stock variables. Further, any parameters controlling lagged adjustment between periods must be divided by four.

3.2.1 Capital accumulation

In comparative-static GTAP, the capital stock used by firms in each region is fixed. To move to a dynamic framework with annual periodicity, an equation linking capital stocks between periods is added

$$K_r^{t+1} = K_r^t + I_r^t - D_r^t; \quad (5)$$

where K_r^t is the quantity of capital available for use in region r in year t , I_r^t is the quantity of new capital created (i.e., investment) in region r during year t , and D_r^t is depreciation of existing capital in region r . With I_r^t and D_r^t representing annual values, K_r^t in

⁵ Dynamic-recursive models are also referred to as sequenced dynamic models, e.g., Hamilton and Whalley (1985) and references cited therein.

(5) will grow at an annual rate. From the perspective of the stock-flow relationship for physical capital in an annual model, equation (5) is all that is required to link capital stocks across periods.

To move to quarterly periodicity, it is necessary to define a quarterly rate of capital accumulation (signified here by superscript q rather than t),

$$K_r^{q+1} = K_r^q + I_r^q - D_r^q. \quad (6)$$

In deriving (6), quarterly values for depreciation, D_r^q , and investment, I_r^q , are created that ensure K_r^q accumulates at a quarterly rate. That is, $D_r^q = D_r^t/4$ and $I_r^q = I_r^t/4$; the determination of I_r^t is explained below.

In the annual and quarterly models, K_r^t and K_r^q reflect past decisions by firms and thus are given by data, so $K_r^t = K_r^q$. The quarterly model uses the same base year data as the annual model, but it applies quarterly values for depreciation and investment to determine the quarterly rate of growth of the capital stock in the initial solution. That is, if the initial solution in the annual model is for 2010, then the first period of the model simulation is 2011. In this case, the quarterly model will also use 2010 data as the initial solution, but in applying quarterly values for depreciation and investment the initial data period is reinterpreted as the last quarter of 2010 (2010:4) and the first period of the model simulation becomes the first quarter of 2011 (2011:1). This flexibility in calibrating the initial solution is important because the initial solution (predominantly input-output data) is usually only available in annual form.

An alternative strategy is to convert the input-output data from annual to quarterly values and to continue to use the initial model theory. Then, all periods are reinterpreted as quarters rather than years. The disadvantage of such an approach is that the periodicity of the model is not obvious except by investigation of the model data. Further, converting the model data from annual to quarterly must be redone for each new data set. In contrast, the approach outlined above requires that the model theory be modified only once. It is also possible to easily switch between annual and quarterly behaviour by defining a parameter, P , that represents the number of subperiods in a year, i.e., $P = 1$ for annual periodicity and $P = 4$ for quarterly periodicity. Then, the quarterly values for depreciation, D_r^q , and investment, I_r^q , used in the quarterly capital accumulation relationship in (6), are defined as $D_r^q = D_r^t/P$ and $I_r^q = I_r^t/P$. In this way, (6) could reflect quarterly accumulation when $P = 4$ or annual accumulation when $P = 1$. In the latter case, (5) is redundant.

3.2.2 Investment

The investment-capital ratio in each region I_r^t/K_r^t is assumed to be a function of the rate of return:

$$\frac{I_r^t}{K_r^t} = (ROR_r^t)^\gamma \cdot F_r^t; \quad (7)$$

where ROR_r^t is the net (of depreciation) post-tax rate of return on capital in the r -th region, and γ is a positive parameter. F_r^t is a region-specific positive constant that ensures that the two sides of (7) are equal given the chosen value of γ and the initial values of ROR_r^t . Equation (7) ensures investment-capital ratios will be higher in regions with higher rate rates of return and vice versa; a constant rate of return will mean a constant growth rate of capital. The parameter $\gamma = 0.5$, which means that the investment-capital ratio will rise (fall) more slowly than the rate of return reflecting increasing costs of adjusting the capital stock by larger amounts: see Figure 2. This treatment captures the inertia in investment behaviour as observed in empirical studies.⁶

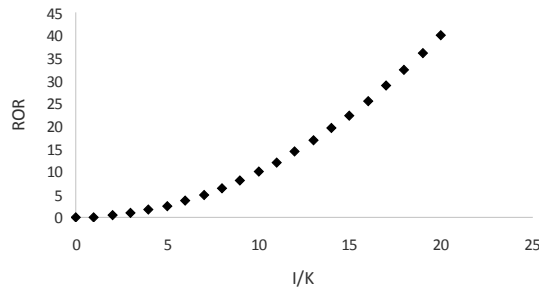


Figure 2. Investment-capital schedule

Equation (7) determines investment responses for annual periodicity. An equation of the same form determines investment responses for quarterly periodicity:

$$\frac{I_r^q}{K_r^q} = (ROR_r^q)^\gamma \cdot F_r^q. \quad (8)$$

In contrast to (7), (8) applies quarterly investment-capital ratios and rates of return. In moving from (7) to (8) it seems that the planning horizon for the firm has now changed from annual to quarterly. But this is not true. In a recursive-dynamic framework as applied here, expectations by investors are myopic. Thus, if they extrapolate ROR_r^q forward by four quarters to give the change in the rate of return over a year ROR_r^t , they calculate

⁶ See Chirinko (1993) for a survey of approaches to modelling inertia in investment behaviour.

$(1 + ROR_r^t) = (1 + ROR_r^q)^4$ or $ROR_r^t = (1 + ROR_r^q)^4 - 1$. In this case, the growth rate in ROR_r^t is approximately equal to four times the growth rate in ROR_r^q . Similarly, the relationship between quarterly investment and annual investment is $I_r^t = 4I_r^q$, which also gives nearly equivalent growth rates. This means that there is no difference between a quarterly and annual planning horizon for investors. Note that this is not true in an intertemporal framework where investors have model-consistent expectations, so that they know the value of ROR_r^q in future periods and this may diverge from the value of ROR_r^q in the current period.

3.2.3 Labour supply and labour-market clearing

The GTAP model defines two types of labour: skilled and unskilled. Thus, here labour supply is specified by labour type and is assumed to be sensitive to the real wage consistent with international evidence on non-zero wage elasticities of labour supply (e.g., Bargain *et al.*, 2011):

$$\frac{LS_{lr}^t}{POP_r^t} = (RW_{lr}^t)^\beta \cdot A_{lr}^t. \quad (9)$$

Thus the supply of labour type l in each region in year t , LS_{lr}^t , is determined as a function of population in year t , POP_r^t , and the post-tax wage received by labour type l in region r in year t , RW_{lr}^t . A_{lr}^t and β are positive constants. With the uncompensated labour supply elasticity $\beta = 0.15$, labour supply is only slightly responsive to the real return to labour in each region. A_{lr}^t is a positive constant that is set to ensure equality between each side of (9) in the initial solution. Note that a similar relationship to (9) applies in the quarterly model.

3.2.4 Labour market adjustment

In comparative-static GTAP, employment of each labour type in each region in year t , LD_{lr}^t , is fixed. With LS_{lr}^t now defined in (9), LD_{lr}^t is made endogenous by specifying a mechanism that determines period-to-period adjustment of wage rates as follows:

$$\Delta W_{lr}^t = \Delta W_{lr}^{t-1} (1 + INF_r^t) + \Delta INF_r^t \cdot W_{lr}^{t-1} + \alpha_{lr}^t (\Delta LD_{lr}^t - \Delta LS_{lr}^t) + F_{lr}^t; \quad (10)$$

where W_{lr}^t is the wage rate in year t , INF_r^t is the inflation rate in year t , LD_{lr}^t is labour demand (employment) in year t , α_{lr}^t is a positive parameter, and F_{lr}^t is a positive constant. With an approximately constant unemployment rate ($\Delta LD_{lr}^t = \Delta LS_{lr}^t$), wage rates will grow at the rate of inflation from year $t-1$ and t . Where $\Delta LD_{lr}^t \neq \Delta LS_{lr}^t$, wage rates will grow more (less)

quickly than the inflation rate if the unemployment rate is falling (rising). The rate of wage adjustment per period is controlled by α , where

$$\alpha_{lr}^t = \begin{cases} 0.5 : UR_{lr}^t / UR_{lr}^{LR} \geq 1 \\ 1.0 : UR_{lr}^t / UR_{lr}^{LR} < 1 \end{cases}.$$

This means the rate of wage adjustment per period depends on labour market conditions relative to the longrun unemployment rate. When the unemployment rate in any period UR_{lr}^t is above its longrun level UR_{lr}^{LR} , wage adjustment will be slower and employment adjustment will be faster reflecting slackness in the labour market. When the unemployment rate is below its longrun level, wage adjustment will be faster and employment adjustment will be slower reflecting tightness in the labour market. This is consistent with empirical evidence that the rate of wage adjustment is partially determined by non-Walrasian features of the economy (see Romer (2001), chapter 9). Consistent with this idea, McKibbin and Wilcoxon (1999) argue that representing wage rates as slowly adjusting provides a more realistic transition from the shortrun to the longrun. Note that a similar relationship to (10) applies in the quarterly model. In the longrun wage rates adjust to ensure the unemployment rate is returns to its longrun level.

3.2.5 Data

The model is calibrated using the GTAP database (Narayanan and Walmsley, 2008). The data are aggregated to 27 regions and 30 sectors (Table 1). Besides the parameter values discussed in earlier sections, many of the original GTAP values for other parameters are adopted with a few exceptions (Table 2).

Table 1. Regions and sectors in model database

Region	Sector
1. Australia	1. Agriculture
2. Rest of Oceania	2. Coal
3. China	3. Oil
4. Japan	4. Gas
5. Korea	5. Other minerals
6. India	6. Processed food
7. Indonesia	7. Beverages and tobacco products
8. Singapore	8. Textiles, wearing apparel
9. Rest of Asia	9. Leather, wood products
10. Canada	10. Paper products, publishing
11. United States of America	11. Petroleum, coal products
12. Mexico	12. Chemicals, rubber, plastics
13. Argentina	13. Other mineral products
14. Brazil	14. Metals, metal products
15. Rest of South & Central America, Caribbean	15. Motor vehicles and parts
16. France	16. Other transport equipment
17. Germany	17. Electronic equipment
18. Italy	18. Other manufacturing
19. Great Britain	19. Utilities
20. Rest of European Union	20. Construction
21. Rest of Europe	21. Wholesale & retail trade
22. Russia	22. Air transport
23. Former Soviet Union	23. Other transport
24. Turkey	24. Communication
25. Rest of Middle East, North Africa	25. Other financial services
26. South Africa	26. Insurance
27. Rest of Sub-Saharan Africa	27. Other business services
	28. Recreation, other services
	29. Government services
	30. Dwellings

3.2.6 Generating model results

In a dynamic model simulation of the effects of a pandemic, the model is run twice to create the baseline and policy scenarios. The baseline here is intended to begin from an observed equilibrium (2004) that evolves to a balanced growth path. The policy scenario comprises the baseline scenario plus the policy shock of interest, i.e., the pandemic. The starting data is updated from 2004 to 2009 by incorporating historical movements in real GDP and labour supply.⁷ From 2010 to 2015 we apply historical population movements, and assume 2% annual growth in labour productivity and fixed factors (land and natural resources) in all regions. Although initial investment-capital ratios are not at steady-state levels in each region, i.e., they do not equal the rate of return on capital, the assumptions for growth in labour productivity and fixed factors mean that all quantity variables converge to grow at the longrun growth rate for each region: population growth plus the growth in labour productivity.

⁷ The GDP data are sourced from the International Monetary Fund's World Economic Outlook Database. The labour supply data are sourced from the International Labour Organization's Labour Statistics Database.

Table 2. Model parameter values

Sector	Elasticity of substitution across:				
	domestic & imported goods	imported goods from different regions	goods consumed by government	intermediate inputs used by firms	factors of production
1. Agriculture	2.37	4.77	0.5	0.1	0.22
2. Coal	3.05	6.10	0.5	0.1	0.20
3. Oil	5.20	10.40	0.5	0.1	0.20
4. Gas	5.20	10.40	0.5	0.1	0.20
5. Other minerals	0.90	1.80	0.5	0.1	0.20
6. Processed food	2.72	5.59	0.5	0.1	1.12
7. Beverages and tobacco products	1.15	2.30	0.5	0.1	1.12
8. Textiles, wearing apparel	3.73	7.46	0.5	0.1	1.26
9. Leather, wood products	3.58	7.30	0.5	0.1	1.26
10. Paper products, publishing	2.95	5.90	0.5	0.1	1.26
11. Petroleum, coal products	2.10	4.20	0.5	0.1	1.26
12. Chemicals, rubber, plastics	3.30	6.60	0.5	0.1	1.26
13. Other mineral products	2.90	5.80	0.5	0.1	1.26
14. Metals, metal products	3.55	7.23	0.5	0.1	1.26
15. Motor vehicles and parts	2.80	5.60	0.5	0.1	1.26
16. Other transport equipment	4.30	8.60	0.5	0.1	1.26
17. Electronic equipment	4.40	8.80	0.5	0.1	1.26
18. Other manufacturing	3.99	8.03	0.5	0.1	1.26
19. Utilities	0.00	0.00	0.5	0.1	1.26
20. Construction	0.50	1.00	0.5	0.1	1.40
21. Wholesale & retail trade	0.10	0.10	0.5	0.1	1.68
22. Air transport	1.90	3.80	0.5	0.1	1.68
23. Other transport	0.50	1.00	0.5	0.1	1.68
24. Communication	0.00	0.00	0.5	0.1	1.26
25. Other financial services	0.00	0.00	0.5	0.1	1.26
26. Insurance	0.00	0.00	0.5	0.1	1.26
27. Other business services	0.00	0.00	0.5	0.1	1.26
28. Recreation, other services	0.10	0.10	0.5	0.1	1.26
29. Government services	0.00	0.00	0.5	0.1	1.26
30. Dwellings	0.00	0.00	0.5	0.1	1.26

4. Modelling pandemic influenza⁸

4.1 The infectious disease model

The morbidity and mortality impact of the pandemic on the age cohorts of the population are taken from Verikios *et al.* (2016) who model them using a variation on the classic Susceptible-Exposed-Infected-Recovered (SEIR) model of infectious disease transmission (Anderson and May, 1992). The SEIR Model computes the theoretical number of people infected with an infectious disease in a closed population over time. This type of modelling is applicable to diseases where an individual that has recovered from the disease is removed from the susceptible population. In order to derive the equations of the model, the population of a single region or demographic group is divided into eight subpopulations: susceptible, vaccinated, exposed, three subsets of infected (untreated, hospitalised, and treated), recovered, and dead. Figure 2 displays the way the model replicates the dynamics of a pandemic.

⁸ This section draws on Verikios *et al.* (2016), sections 3 and 4.

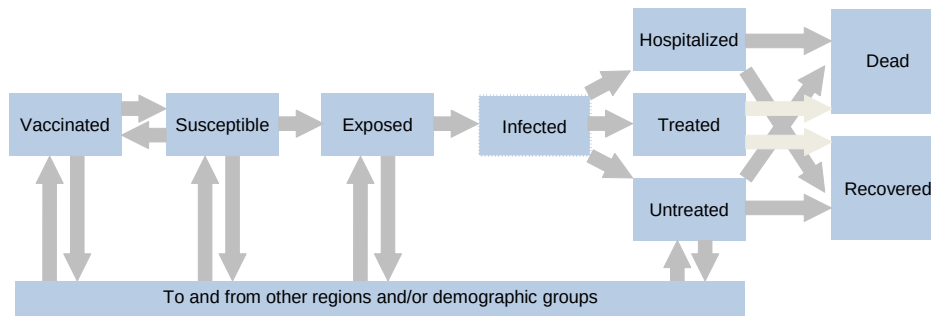


Figure 2. The SEIR model

The susceptible population is decreased through vaccination and exposure to the virus; conversely, it is increased by the loss of vaccine-acquired immunity. Vaccinated individuals are not considered to be completely protected but become exposed at a rate much lower than the susceptible population. Vaccine efficacy can vary over the course of the epidemic. Typically, around one month is required after vaccination until the individual has produced sufficient antibodies for the vaccine to be effective. Even after this initial time period, vaccine efficacy will be less than 100% due to varying individual antibody response to vaccine and the possibility of viral mutation or an imperfectly-matched vaccine. A different vaccine efficacy is assumed in each scenario.

After exposure, individuals progress to one of three infected states: untreated, treated, and hospitalised. The proportion of individuals progressing into each category is dependent on viral characteristics. As the virulence of the virus increases, the proportion of the infected receiving treatment also increases. The duration of infectiousness and transmission probabilities are decreased for those receiving treatment. Through this mechanism the parameters of the model allow for the simulation of behavioural and medical quarantine.

An increase in virulence can result in a reduction of average transmissibility; individuals with a severe virus tend to be too ill to be out in the community transmitting the virus. In addition, those receiving treatment or who are hospitalised will have reduced contact and transmissibility due to precautionary measures such as masks, gloves, and isolation. Individuals remain infectious during the entire course of their clinical infection. Once they have progressed out of the infectious state they can no longer transmit the virus to others.

After infection, individuals progress to one of two groups: recovered or dead. The rate at which individuals progress from one of the three infected states (hospitalised, treated, or untreated) to the end states is dependent on virulence and the level of treatment during infection. Hospitalised individuals have the highest death rate, followed by treated and untreated cases. Many of the untreated individuals likely have subclinical or asymptomatic

infections, which reduces death rates despite the fact that some with untreated clinical infections may be more likely to die.

Those individuals progressing to the recovered state are considered to have immunity for the duration of the pandemic. Pandemics tend to come in waves and infect geographic areas for short periods of time. It is unlikely that in the case of an influenza pandemic the strain will mutate enough to cause re-infection during a single pandemic wave. There are five morbidity states included in the pandemic model:

1. subclinical, where the infected person seeks no medical attention but purchases pharmaceuticals;
2. physician and flu clinic, where the infected person seeks medical attention by visiting a physician or a flu clinic;
3. hospitalisation, where the infected person is hospitalised and survives;
4. intensive care unit (ICU), where the infected person is hospitalised and spends time in an ICU and survives; and
5. death, where the infected person is hospitalised and dies.

4.2 The influenza scenario

The influenza pandemic applied here is drawn from Verikios *et al.* (2016).⁹ The scenario begins in Vietnam and has a global fatality impact of around 0.01%. It is an extremely transmissible influenza virus with a global attack rate of approximately 40%, despite the availability of an effective vaccine within months of the outbreak. The case fatality rate is 0.5%, which is similar to the case fatality rate of the 1957 influenza pandemic. Unlike seasonal influenza where typically 90% of the fatalities are observed in individuals greater than 65, this virus has an equal case fatality across ages consistent with the 2009 H1N1 pandemic. The majority of cases are subclinical or physician visits and approximately one-fifth of those hospitalised require intensive care, analogous to what is observed in seasonal outbreaks.

The pandemic scenario has viral characteristics that are plausible but less extreme than historical events, such as the 1918 pandemic. Figure 3 shows how the pathogen characteristics of the scenario compare to historical flu pandemics. Epidemic curves were created for each country or region using the calculated correlation between the observed 2009 H1N1 pandemic transmission timeline and country density. A log-linear relationship between population and weeks until pandemic peak represented the most appropriate statistical fit.

⁹ This scenario is referred to as ‘Event 2’ in Verikios *et al.* (2016).

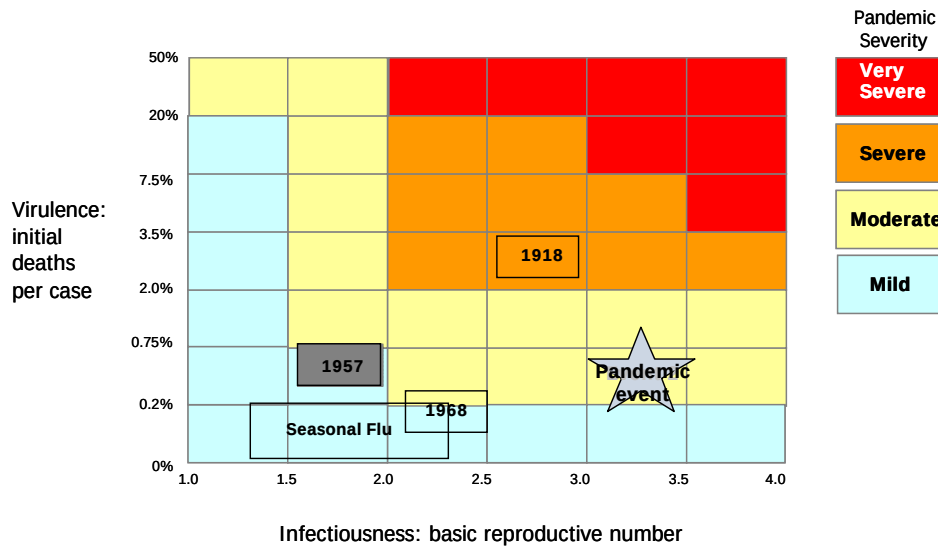
The epidemic curves were used to develop weekly totals of individuals in each of the six morbidity classes by country or region.

4.2.1 Morbidity and mortality

The SEIR model provides estimates of the number of persons newly infected per week and the severity of their infection in each region over the course of the pandemic year. The modelled scenario provides the number of infection types for the total population and the working-age population by country or country grouping. Figure 4 compares the severity of the pandemic across regions on the basis of the proportion of the population that is assumed to be infected with influenza. Overall infection rates are high relative to previous pandemics: see the x-axis in Figure 3. Further, infection rates are higher in lower income countries than in higher income countries, and higher in Asian regions, where the pandemic is assumed to begin, than in non-Asian regions. Given these very high infection rates, it is likely that the inevitable ‘quarantine-like’ (social exclusion) measures to prevent the spread of the virus may be rather important in determining the economic effects.

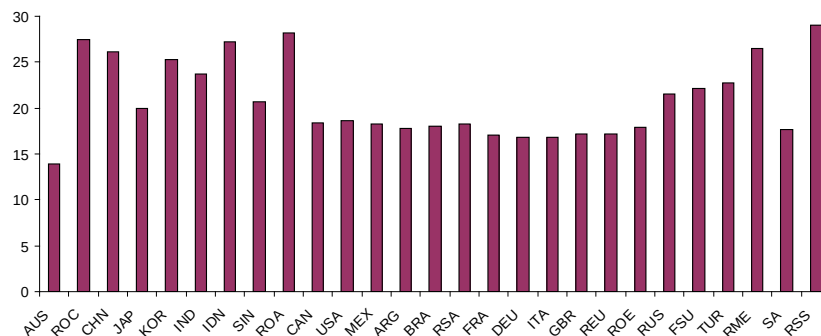
Figure 5 plots the distribution of infected cases by severity; it shows that the distribution of infections is skewed towards less severe cases and only a small proportion of infections result in death (0.5%). In historical terms, the pandemic’s virulence (i.e., initial deaths per case) is similar to previous pandemics as shown on the y-axis in Figure 3. Therefore, the majority of cases remain at the subclinical and physician/flu clinic levels of contact with the health system. Other things being equal, this will tend to make the reduction in the labour supply (due to deaths) relatively unimportant in determining the direct economic effects.

Figures 6 and 7 present a picture of the dynamics of the influenza outbreak; the picture is typical of historical influenza pandemics. Globally, new infections occur over about two-thirds (about 35 weeks) of the year. New infections peak around week 16, and there are two further smaller peaks around weeks 22 and 32. The pattern of global new infections overstates the short, sharp nature of the outbreak at the regional level. Figure 7 shows that new infections last for only around 10 weeks in each region, on average. It also shows how the outbreak moves from continent to continent depending on travel patterns across continents. Thus, the outbreak begins in Rest of Asia (Vietnam), moves quickly to China, then the United States and Africa, and lastly to South America. These dynamics of the outbreak will be important in determining the timing of economic effects across regions. The economic aspects of the outbreak’s dynamics can not be captured by an economic model that does not also reflect these dynamics, i.e., periodicity of much less than one year.



Notes: Virulence is measured in terms of the case-fatality rate or deaths per infected case. Infectiousness (or transmissibility) represents the speed at which a pandemic will spread within a population and the total number of people that will be infected. Infectiousness of influenza is measured by the basic reproductive rate (R_0), or the mean number of secondary cases an infectious case will cause in a population without immunity and without intervention. $R_0 > 1$ is necessary for an epidemic to occur.

Figure 3. Pathogen characteristics of the modelled pandemic relative to historical pandemics



Legend: Australia (AUS), Rest of Oceania (ROC), China (CHN), Japan (JPN), Korea (KOR), India (IND), Indonesia (IDN), Singapore (SIN), Rest of Asia (ROA), Canada (CAN), United States of America (USA), Mexico (MEX), Argentina (ARG), Brazil (BRA), Rest of South America (RSA), France (FRA), Germany (DEU), Italy (ITA), Great Britain (GBR), Rest of European Union (REU), Rest of Europe (ROE), Russia (RUS), Former Soviet Union (FSU), Turkey (TUR), Rest of Middle East (RME), South Africa (SA), Rest of Africa (RSS).

Figure 4. Infection rates by region (% of population)

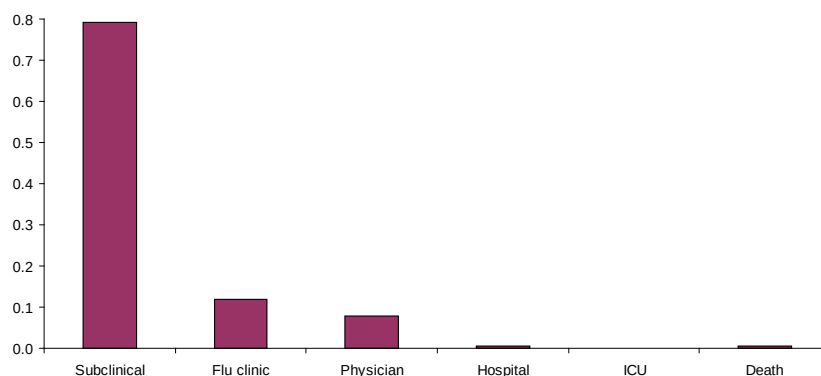


Figure 5. Distribution of cases by severity (% of total infections)

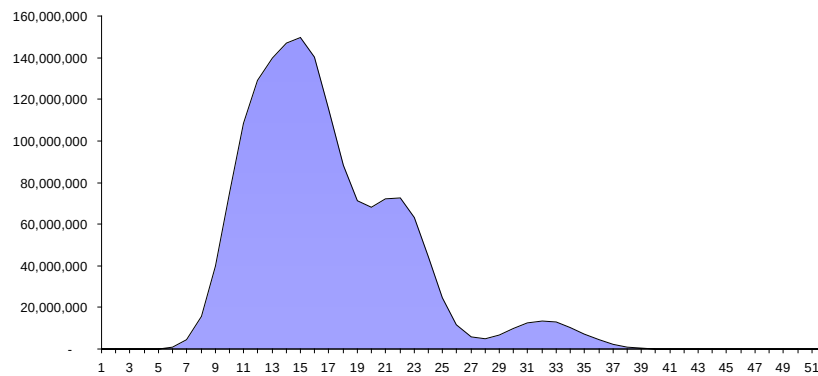


Figure 6. New infections per week in the global population

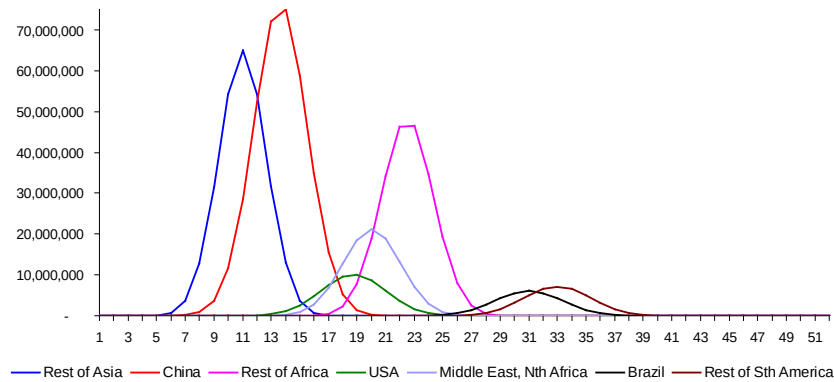


Figure 7. New infections per week in selected regional populations

4.3 The economic shocks

Previous analysis of pandemics and their potential economic effects highlight a number of channels through which an economy might be affected by a serious outbreak of influenza.¹⁰ These channels include: reduced consumption by households on tourism, transportation and retail spending; increased absence from the workplace due to illness or for prophylaxis; school closures; and higher demands for medical services. Considering these channels, four types of economic shocks are applied to simulate the influenza pandemic.

1. A temporary surge in demand for hospital and other medical services. Increased medical spending related to each pandemic is applied as increased expenditure on the *Government services* sector.

¹⁰ See Chou *et al.* (2004), Congressional Budget Office (2006). Dixon *et al.* (2010), Fan (2003), James and Sargent (2006), Jonung and Roeger (2006), Keogh-Brown *et al.* (2010), Lee and McKibbin (2004). McKibbin and Sidorenko (2006) and Verikios *et al.* (2012).

2. A temporary upsurge in sick leave and school closures requiring withdrawal of parents from the labour force. These effects are modelled as a temporary decrease in output per worker (labour productivity).
3. Some deaths with a related permanent reduction in the labour force.
4. Temporary reductions in inbound and outbound international tourism and business travel that are a function of the number of persons infected and the initial deaths per case. The shocks to tourism are applied to exports of four sectors: *Wholesale and retail trade, Air transport, Other transport, and Recreation and other services*.

These shocks are explained in detail in Verikios *et al.* (2016).

5. Economic modelling of pandemic influenza with variable periodicity

5.1 Quarterly modelling

In this section we apply the direct effects of the pandemic onto the quarterly economic model. Figure 8 reports the effects on the levels of selected global variables relative to baseline; Table 3 reports the real GDP effects for all regions.

The main impacts occur in 2010, the pandemic year. In quarter 1 of 2010 (2010:1) the pandemic causes global GDP to fall by 0.8% and labour by 1.2%. In 2010:2, GDP and labour fall further (-3% and -4.2%) as new infections continue to rise (see Figure 6). As new infections peak in 2010:2, so too do the negative effects on GDP and labour. The movements in GDP are mostly driven by movements in labour. Labour is the only variable input in the short run as capital stocks are subject to a one period gestation lag. The contractionary effect of the pandemic reduces demand for labour by firms. As wage rates are sticky in the short run, they do not fall enough to maintain labour usage thus causing the fall in labour to be greater than would otherwise be case.

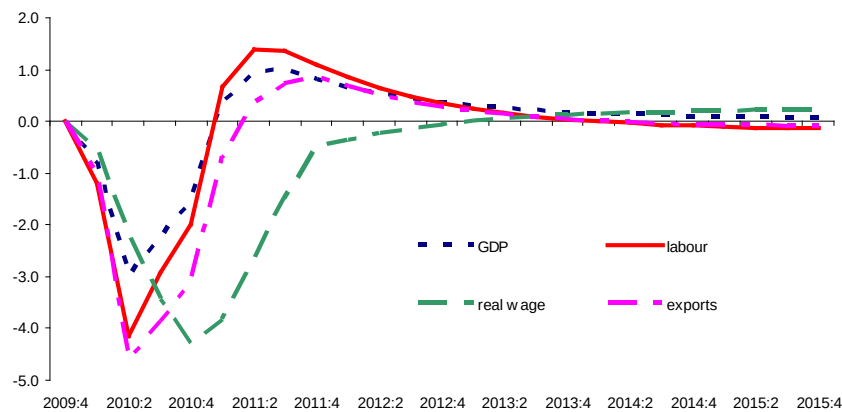


Figure 8. Quarterly model effects on selected global variables (percentage difference in levels relative to baseline)

Table 3. Quarterly model effects on global and regional GDP (percentage difference in levels relative to baseline)

Region	Quarter							
	2010:1	2010:2	2010:3	2010:4	2011:1	2011:2	2011:3	2011:4
World	-0.80	-2.97	-2.23	-1.54	0.39	0.96	0.98	0.81
Australia	-0.57	-2.51	-2.03	-1.38	0.41	0.98	1.00	0.77
Rest of Oceania	-0.54	-2.27	-1.85	-1.35	0.26	0.82	0.82	0.73
China	-1.51	-5.68	-4.58	-3.59	0.36	1.95	2.18	1.79
Japan	-0.84	-2.59	-1.90	-1.21	0.53	0.99	0.96	0.75
Korea	-1.13	-3.62	-2.83	-2.00	0.27	1.16	1.39	1.26
India	-0.09	-0.74	-0.56	-0.31	0.31	0.42	0.41	0.35
Indonesia	-0.70	-2.50	-1.94	-1.41	0.25	0.93	1.10	1.02
Singapore	-2.40	-7.35	-5.84	-4.52	-0.31	1.84	2.60	2.53
Rest of Asia	-0.65	-3.22	-2.53	-1.87	0.02	0.66	0.95	0.85
Canada	-0.76	-3.19	-2.33	-1.69	0.42	1.07	0.99	0.79
United States	-0.52	-1.86	-1.24	-0.64	0.48	0.52	0.40	0.32
Mexico	-0.08	-0.50	-0.31	-0.15	0.23	0.37	0.37	0.34
Argentina	-0.57	-2.24	-1.75	-1.25	0.12	0.63	0.75	0.62
Brazil	-0.25	-1.07	-0.71	-0.50	0.28	0.50	0.47	0.45
Rest of South America	-0.42	-1.99	-1.49	-1.04	0.30	0.69	0.71	0.56
France	-1.01	-3.83	-2.78	-1.91	0.60	1.30	1.25	0.96
Germany	-1.06	-3.92	-2.85	-1.96	0.50	1.26	1.29	1.04
Italy	-0.54	-2.21	-1.73	-1.26	0.23	0.70	0.77	0.64
Great Britain	-1.21	-4.40	-3.28	-2.29	0.63	1.52	1.49	1.16
Rest of EU	-1.38	-5.07	-4.06	-3.16	0.13	1.46	1.70	1.41
Rest Europe	-0.84	-3.07	-2.26	-1.50	0.39	0.96	1.07	0.92
Russia	-0.46	-2.05	-1.71	-1.31	0.05	0.65	0.89	0.90
Former Soviet Union	-0.60	-2.68	-2.18	-1.62	0.10	0.70	0.84	0.75
Turkey	-0.10	-0.74	-0.59	-0.38	0.04	0.16	0.27	0.30
Rest of Middle East	-0.26	-1.45	-1.08	-0.71	0.31	0.55	0.55	0.51
South Africa	-0.51	-2.13	-1.56	-1.12	0.26	0.71	0.70	0.60
Rest of Africa	-0.41	-2.37	-1.87	-1.48	0.13	0.67	0.65	0.52

In 2010:3 the number of new global infections falls significantly as there are no new infections in Asia (the origin of the virus) and Europe; in 2010:4 there are only a small number of new infections and these are in Australia and South America. Although there are few new infections in 2010:3 and 2010:4, the pandemic keeps global economic activity depressed due to continuing precautionary measures (e.g., voluntary and imposed restrictions on travel, prophylactic absenteeism by workers) to prevent the spread of the virus until no new infections are observed in a region. Nevertheless, economic activity begins to recover over 2010:3-4 as real wage rates respond with a lag to the fall in labour demand in 2010:1 and 2010:2. The delayed response of real wage rates begins to clear the excess supply in the labour market and so GDP and labour show smaller negative deviations from baseline in 2010:3 (-2.2% and -2.9%) and 2010:4 (-1.5% and -2%) compared to 2010:1 and 2010:2.

To understand the effects of the four categories of shocks on global GDP, Figure 9 shows the individual effect of each shock on global GDP relative to baseline. In 2010, the increase in medical services (due to hospitalisations and treatments), the reductions in labour supply (due to deaths) and labour productivity (due to lost workdays), and the fall in international tourism have negative effects on GDP. Of these shocks, the fall in international

tourism dominates; the peak effect here is -2.8%, which accounts for most of the peak GDP effect of -3% in 2010 for all shocks combined. The importance of the tourism effects is also reflected in Figure 8 as large negative effects on global exports. The effect on exports is dominated by the fall in international tourism due to the pandemic.

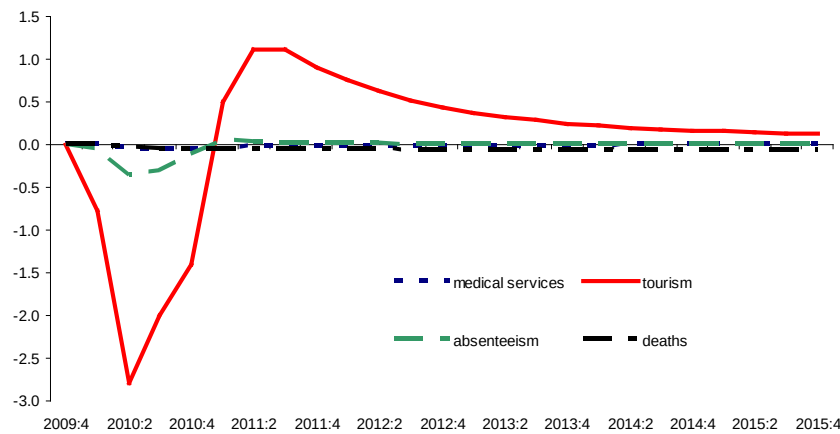


Figure 9. Quarterly model effects of individual shocks on global GDP (percentage difference in level relative to baseline)

Figure 9 shows that the temporary reduction in international tourism dwarfs all other effects. The pandemic evaluated here has a relatively high global infection rate in historical terms (24%). As discussed in Section 4.2, the infection rate is the dominant determinant of the size of the tourism reductions. This characteristic of the pandemic causes the tourism effects of this pandemic to be very large.

Beginning in 2011:1, the exogenous shocks representing the pandemic are slowly withdrawn and this process is complete by 2011:4. Thus, Figure 8 shows GDP and labour move above baseline in 2011:1 by 0.4% and 0.7%. In 2011:2 and 2011:3, GDP and labour continue to move above baseline. This is due to the lagged response of wage rates to the end of the pandemic; this means that real wage rates are still 0.5% below baseline in 2011:4 as they only adjust slowly to the change in labour market conditions. From 2012:1 employment and GDP move back towards baseline as real wage rates also move back towards baseline. By 2015 employment and real GDP return close to baseline levels.

Figure 10 presents the GDP effects relative to baseline for selected regions. All regions are projected to experience lower output in the shortrun (Table 3); the differences across regions are purely due the size of the negative output effects. Singapore experiences the largest negative deviation in 2010 real GDP: -7.3% in 2010:2. The very large effect on Singapore's GDP is due to the strong negative effect on global trade (exports; see Figure 8) from the pandemic rather than the direct impact of reduced inbound tourism to Singapore.

Singapore is an entrepot port through which large volumes of goods and persons pass on the way to their final destination. This is reflected in export and import to GDP shares of around 150% in the base data. Thus, Singapore is the region most exposed to the contraction in global trade due to its unique transit status.

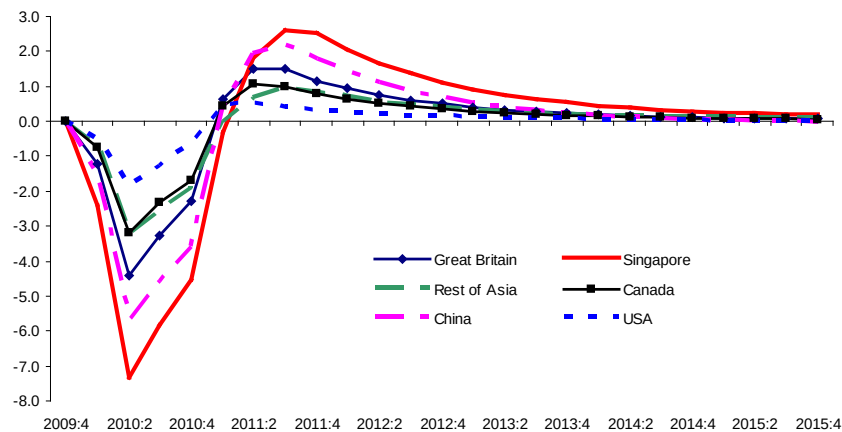


Figure 10. Quarterly model GDP effects for selected regions (percentage difference in levels relative to baseline)

Other countries with high trade-to-GDP shares also experience a strong negative indirect effect on their GDP due to the contraction in global trade. However, the size of international tourism in GDP is also important for determining the GDP effects for other countries. Thus, China (-5.7%), Great Britain (-4.4%), Canada (-3.2%) and Rest of Asia (-3.2%) experience relatively large peak GDP effects (2010:2). Whereas USA (-1.9%), Brazil (-1%) and India (-0.7%) experience smaller peak GDP effects.

5.2 Annual modelling

In this section we apply the direct effects of the pandemic (i.e., the shocks) onto the annual economic model. In doing so, the shocks applied are annualised changes of the quarterly shocks applied to the quarterly model. To give a flavour of how the annual shocks are calculated from the quarterly shocks, Table 4 shows how the quarterly inbound tourism shocks for China and Australia are converted to annual shocks over 2010.

Table 4. Quarterly and annual tourism shocks for China and Australia

Period	Level of tourism flow relative to baseline		Quarterly shock (percentage change)		Annual shock (percentage change)	
	China	Australia	China	Australia	China	Australia
2010						
Q1	0.861	1.000	-13.88	0.00		
Q2	0.726	0.998	-15.68	-0.21		
Q3	0.726	0.848	0	-15.03		
Q4	0.726	0.844	0	-0.49		
Total	3.040	3.689	-29.56	-15.73	-24.01	-7.76

In 2010:1 and 2010:2, there is a 14% and 16% fall in inbound tourism for China based on the number of new infections in those quarters. As there are no new infections in 2010:3 and 2010:4, inbound tourism remains depressed but does not fall further relative to baseline. Assuming baseline tourism flows are 1 for each quarter, the reduced level of tourism for the year is 3.04 ($= 0.861 + 0.726 + 0.726 + 0.726$). Relative to a baseline flow of 1 per quarter, this represents a cumulative reduction of 29.56% for the year. The annual shock will be -24.01% representing the annual flow of 3.040 relative to a baseline flow of 4. For China the annual shock is 81% ($= 24.01/29.56$) of the cumulative sum of the quarterly shocks. Similar calculations for Australia give an annual shock that is 49% ($7.76/15.73$) of the cumulative sum of the quarterly shocks.

These differences in the size of the relative quarterly and annual shocks will strongly affect the degree to which the annual model will misrepresent the size of the direct effects of the pandemic. For China, the quarterly shocks and annual shocks will give similar peak effects: -29.56% viz. -24.01%. For Australia, the quarterly shocks and annual shocks will give very different peak effects: -15.73% viz. -7.76%. For Australia, the averaging of the shocks over the year underestimates the effect on the economy from the pandemic by about 50%. The degree of misrepresentation depends on the timing of the shocks through the year. For China, all of the effect occurs in the first half of the year. For Australia, most of the effect occurs in the second half of the year. By construction, these differences in the time profile of the pandemic can not be captured by the annual model.

The annual shocks are applied to the annual model: Figure 11 compares the peak GDP effects of the quarterly and annual models. The peak GDP differences are significant: as an overall measure, the global GDP deviation peaks at -3% in 2010:2 in the quarterly model and -1.2% in the annual model. Table 5, column 4, presents the ratio of the annual to quarterly peak effects. The simple average of these ratios for all regions is 0.41. Thus, the annual model underestimates the peak effects by about 60%. Comparing results between the two models for the full year (Table 4, column 5), the annual model underestimates the true result by 22% on average. This is still a significant underestimate. The comparison shows the

importance of accurately capturing the time profile of the pandemic when estimating the economic effects.

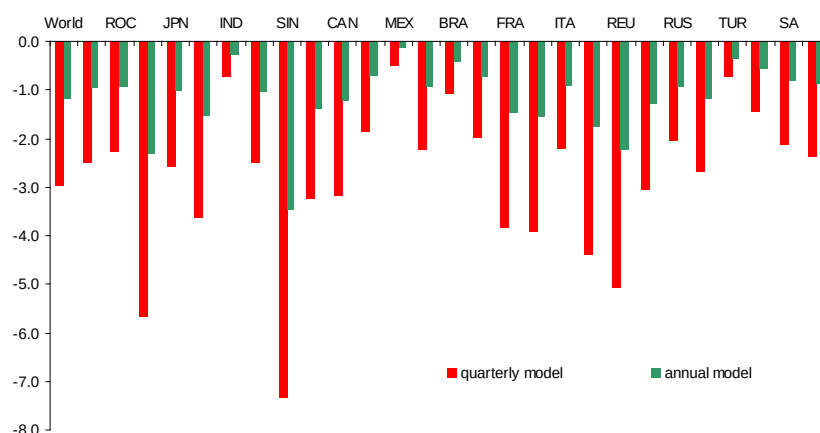


Figure 11. Peak GDP effects of quarterly(2010:2) and annual model (2010) (percentage difference in levels relative to baseline)

At the regional level, the size of the underestimate by the annual model is rather even as reflected by the small standard deviations. The annual model underestimates the peak effects by about 60% for most regions and the full year effects by about 20%. This reflects the strength of the indirect effects of the pandemic that affects most regions regardless of the size of the direct effects of the pandemic on any particular region. Put differently, for most regions the aggregate (or global) effect of the pandemic is strong enough to overwhelm the idiosyncratic (or region-specific) effect of the pandemic. This is a function of the strong negative effects on international tourism of the pandemic. An infectious disease outbreak will discourage travel to all regions but more so to heavily affected regions. Lower tourism exports by affected regions mean lower demand for imports from other regions that may not be heavily affected by the pandemic. For most regions this general equilibrium effect is quite strong. Exceptions to this effect include India, the US, Mexico and Turkey, where the full year effects are mis-estimated by the annual model by 10% or less.

Table 5. Annual model effects on global and regional GDP: absolute and relative to quarterly model

Region	Quarterly model		Annual model	Ratio of annual to quarterly effect at:	
	2010:2	2010:4		2010:2	2010:4
	(1)	(2)	(3)	(4)	(5)
World	-2.97	-1.54	-1.20	0.40	0.78
Australia	-2.51	-1.38	-0.98	0.39	0.71
Rest of Oceania	-2.27	-1.35	-0.94	0.42	0.70
China	-5.68	-3.59	-2.31	0.41	0.64
Japan	-2.59	-1.21	-1.01	0.39	0.84
Korea	-3.62	-2.00	-1.54	0.43	0.77
India	-0.74	-0.31	-0.27	0.37	0.89
Indonesia	-2.50	-1.41	-1.05	0.42	0.74
Singapore	-7.35	-4.52	-3.46	0.47	0.77
Rest of Asia	-3.22	-1.87	-1.39	0.43	0.74
Canada	-3.19	-1.69	-1.21	0.38	0.72
United States	-1.86	-0.64	-0.71	0.38	1.10
Mexico	-0.50	-0.15	-0.15	0.30	0.96
Argentina	-2.24	-1.25	-0.92	0.41	0.74
Brazil	-1.07	-0.50	-0.42	0.39	0.85
Rest of South America	-1.99	-1.04	-0.74	0.37	0.71
France	-3.83	-1.91	-1.48	0.39	0.77
Germany	-3.92	-1.96	-1.56	0.40	0.80
Italy	-2.21	-1.26	-0.90	0.41	0.71
Great Britain	-4.40	-2.29	-1.76	0.40	0.77
Rest of EU	-5.07	-3.16	-2.23	0.44	0.71
Rest Europe	-3.07	-1.50	-1.28	0.42	0.85
Russia	-2.05	-1.31	-0.95	0.46	0.73
Former Soviet Union	-2.68	-1.62	-1.19	0.44	0.73
Turkey	-0.74	-0.38	-0.37	0.50	0.97
Rest of Middle East	-1.45	-0.71	-0.56	0.39	0.78
South Africa	-2.13	-1.12	-0.82	0.39	0.73
Rest of Africa	-2.37	-1.48	-0.89	0.37	0.60
Average				0.41	0.78
Standard deviation				0.04	0.10

6. Conclusion

Infectious diseases are a leading cause of death worldwide, and infectious disease rates are rising. Previous analysis has demonstrated infectious disease outbreaks can easily cross borders to threaten economic and regional stability (e.g., HIV, H1N1, H5N1 and SARS). The constant adaptation of microbes, along with their ability to evolve and become resistant to antibacterial and antiviral agents, ensures that infectious diseases will continue to be an ever-present and ever-changing threat. Assessing these threats is important for informing households, governments and businesses on the possible economic disruption across regions from infectious disease outbreaks. The present study focusses on pandemic influenza, which is a regularly recurring form of infectious disease in history. The threats are assessed by modelling the effects of a hypothetical but typical influenza pandemic by linking epidemiological and economic models.

An important feature of influenza pandemics is their short, sharp nature; they usually begin and end within a year. Thus, the focus here is on the importance of periodicity in modelling the economic disruption from an influenza pandemic. Previous studies focusing on

the economywide effects of global pandemics apply either a macroeconomic or computable general equilibrium (CGE) models. Macroeconomic models have the advantage of assuming quarterly periodicity that allow them to capture the short, sharp nature of pandemics; they have the disadvantage of a single-sector approach that ignores sectors that are particularly relevant to the study of the economic effects of epidemics (e.g., medical services, inbound and outbound tourism). CGE models have the advantage of identifying multiple sectors in the economy; they have the disadvantage of annual periodicity and so are unable to capture accurately the short, sharp nature of influenza pandemics.

A number of recent studies address the limitations of macroeconomic and CGE approaches by applying CGE models with quarterly periodicity (see Dixon *et al.*, 2010, Verikios *et al.*, 2012 and Verikios *et al.*, 2016). These studies argued that quarterly periodicity is crucial to capturing the short, sharp nature of influenza pandemics. The objective here is to test this proposition by simulating an identical influenza pandemic using annual and quarterly periodicity. To do so, a CGE model is applied that incorporates *variable* periodicity to assess the global and regional economic effects of pandemic influenza under annual and quarterly periodicity.

The influenza pandemic assessed here is drawn from Verikios *et al.* (2016). Applying a quarterly approach, the pandemic begins in quarter 1 of 2010 (2010:1) and leads to global GDP deviation that peaks at -3% in 2010:2. This compares to a global GDP deviation that peaks at -1.2% in the annual model. At the global level, the annual model underestimates the true result by around 60%. In terms of the full year effect, the global GDP deviation is estimated at -1.5% by the quarterly model versus -1.2% by the annual model. Here, the annual model underestimates the true result by around 20%. At the regional level, a similar degree of underestimation is observed for most regions. For Singapore, the quarterly model peak effect is -7.4% versus an annual model peak effect of -3.5%; the quarterly model full year effect is -4.5% versus an annual model full year effect of -3.5%. Other regions experience much smaller quarterly peak effects: China (-5.7%), Great Britain (-4.4%), Australia (-2.5%), and Japan (-2.6%). Nevertheless, for all these regions the annual model underestimates the peak effect by around 60% and the full year effect by around 20%. The results show that the global macroeconomic effects of an influenza pandemic may be significant but are also likely to be short lived. Therefore, the most important aspect of the estimating the economic effects is the magnitude of the peak effects rather than the longrun effects. It is on this aspect that the annual model performs poorly.

Consistent with previous work, our results show that the largest economic impacts of an influenza pandemic are driven by reduced international tourism, due to risk-modifying measures by households and travel restrictions imposed by health authorities, and lost workdays, due to illness or formal social distancing measures designed to contain the virus. The effects on international tourism and lost workdays are a function of the new infections in each region. As the pandemic spreads across regions unevenly, peak infections will be distributed unevenly across the pandemic year for each region. Averaging these uneven effects over the year will represent the time profile of the pandemic for each region. Misrepresenting the time profile of the pandemic misrepresents the response of an economy to the pandemic. This is clearly demonstrated here by modelling a given influenza pandemic with a quarterly and annual model; this is the major contribution of this study. Another contribution is to show formally how quarterly and annual dynamics can be added to comparative-static general equilibrium model.

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