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The Economic Impact of an Influenza Pandemic

by

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Abstract

In this paper we examine the potential impact of an influenza pandemic on the economy. We use historical data to understand how past pandemics affected human health, human behaviour and the economy while also accounting for subsequent relevant economic and social changes. We find that previous pandemics and SARS had limited economic effects and that a 1918-type pandemic would likely reduce annual GDP growth by up to 1 percentage point in the pandemic year. Economic and social changes since 1918 would not likely imply significantly greater impacts today than in 1918. The demand and absenteeism impacts of a pandemic would be unevenly distributed across sectors. Small work units in which employees engage in a high degree of social interaction could expect higher peak absenteeism than larger work units with less social interaction. The natural resilience of market economies as well as reallocations of spending across sectors and across time would tend to mitigate the aggregate economic effects of a pandemic. If a pandemic were to occur, human suffering and loss of life would outweigh economic concerns.

Résumé

Dans le présent document, nous examinons les conséquences que pourrait avoir une pandémie de grippe sur l'économie. Nous utilisons des données historiques pour comprendre comment les pandémies passées se sont répercutées sur la santé et le comportement humain ainsi que sur l'économie, tout en ayant un effet sur les changements économiques et sociaux subséquents considérés. Nous avons découvert que les pandémies précédentes et le syndrome respiratoire aigu sévère (SRAS) ont eu peu d'incidences sur l'économie et qu'une pandémie comparable à celle de 1918 réduirait probablement la croissance du produit intérieur brut (PIB) d'au plus un point de pourcentage durant l'année de la pandémie. Il est peu improbable que les changements économiques et sociaux qui surviendraient aujourd'hui seraient plus graves que ceux qui se sont produits à la suite de la pandémie de 1918. Les répercussions d'une pandémie sur la demande et l'absentéisme se feraient sentir différemment selon les secteurs. Les petites unités de travail où les employés ont de nombreuses interactions sociales pourraient prévoir un plus haut niveau d'absentéisme que les grandes unités de travail à faible taux d'interactions sociales. La capacité de récupération naturelle des économies de marché ainsi que la nouvelle répartition des dépenses entre les secteurs et dans le temps contribueraient à atténuer les effets économiques globaux d'une pandémie. Si une pandémie devait nous frapper, la souffrance humaine et les pertes de vies compteraient davantage que les inquiétudes sur le plan économique.

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1 Issue

The H5N1 virus was first detected in chickens in Scotland in 1959, and again in turkeys in England in 1991. A highly pathogenic form was detected in geese in Guandong province, China in 1996 and in poultry in Hong Kong in 1997. The Hong Kong outbreak was associated with first human cases, with 6 of 18 cases proving fatal. Since 2003, human cases have been reported in Cambodia, Indonesia, Thailand, and Viet Nam. As of October 16, 2006, there have been 256 confirmed human cases of H5N1 and 151 deaths.

Direct contact with infected poultry, or their faeces, is considered the main route of human infection. To date, most human cases have occurred in areas where many households keep small poultry flocks, which often roam freely, sometimes entering homes or sharing outdoor areas where children play (World Health Organization).

According to the World Health Organization (WHO), while changes in the virus since 1997 have affected transmission among domestic and wild birds, they have not had any impact on transmissibility to humans, with human infections remaining rare. The virus does not spread easily from birds to humans or readily from person to person. A new influenza strain can develop into a pandemic (infect many people world-wide) if it is easily transmissible among humans. New influenza strains are by definition those to which people do not have prior immunity. The WHO has issued a phase 3 pandemic alert, meaning that “a new influenza virus subtype is causing disease in humans, but is not yet spreading efficiently and sustainably among humans.”

The high human case mortality associated with H5N1 has led to fears that it may mutate into a form that could be transmissible among humans and that this new virus could spark a pandemic of the severity of that observed in 1918. However, we do not know whether H5N1 will definitely mutate into a human-transmissible form or mix with an existing human influenza virus, nor if it does, how dangerous the new virus would be. The WHO says that “it may be years before a pandemic hits the world, and it may ultimately be sparked by a virus other than H5N1.” While in the past pandemics were thought to have a regular periodicity, this no longer viewed as valid (Dowdle (2006)). The probability of a pandemic occurring at a given point in time is not a function of how much time has passed since the last pandemic.

Taubenberger and Morens (2006) note that:

> Like the 1918 virus, H5N1 is an avian virus though a distantly related one. The evolutionary path that led to pandemic emergence in 1918 is entirely unknown, but it appears to be different in many respects from the current situation with H5N1. There are no historical data, either in 1918 or in any other pandemic, for establishing that a pandemic "precursor" virus caused a highly pathogenic outbreak in domestic poultry, and no highly pathogenic avian influenza virus, including H5N1 and a number of others, has ever been known to cause a major human epidemic, let alone a

> pandemic. We do not know how, and we currently have no way of knowing whether H5N1 viruses are now in a parallel process of acquiring human-to-human transmissibility. Despite an explosion of data on the 1918 virus during the past decade, we are not much closer to understanding pandemic emergence in 2006 than we were in understanding the risk of H1N1 "swine flu" emergence in 1976.

This accords with the view of the WHO that:

> Specific mutations and evolution in influenza viruses cannot be predicted, making it difficult if not impossible to know if or when a virus such as H5N1 might acquire the properties needed to spread easily and sustainably among humans. This difficulty is increased by the present lack of understanding concerning which specific mutations would lead to increased transmissibility of the virus among humans.

A number of studies have argued that a pandemic could have large negative economic impacts. Cooper (2005) argues that supply chains would break down, financial markets would be destabilized, building, real estate and home decorating and furnishing companies would suffer, "trade disruptions would shutter manufacturing plants," and that "depending on its length and severity, its economic impact could be comparable, at least for a short time, to the Great Depression of the 1930s." Cooper (2006) predicts that a mild pandemic would reduce global GDP by 2 per cent while a severe pandemic would reduce GDP by 6 per cent.

McKibbin and Sidorenko (2006) estimate a global GDP impact of –0.8 per cent from a mild 1968-type pandemic and –12.6 per cent from a pandemic with population mortality roughly double that experienced in 1918. They estimate that the mortality effects of such a severe pandemic would be significantly greater in less developed countries, with GDP impacts reaching as high as 50 per cent.

The U.S. Congressional Budget Office (CBO) estimates that a pandemic with population mortality double that of 1918 would reduce U.S. GDP by 5 per cent, while a 1957-type pandemic would reduce GDP by 1.5 per cent. They argue that psychological impacts on consumer demand could be significant.

The IMF Working Group (2006) argues that a severe pandemic could have a sharp but short-lasting impact on the economy. They claim that risk premia could rise, asset markets could be negatively affected and that high rates of absenteeism could cause disruption to the global financial system, including clearing and payments systems.

Bloom *et al.* (2005) of the Asian Development Bank estimate that a relatively mild pandemic could reduce Asian GDP by between 2.6 and 6.8 per cent, depending on the size of assumed psychological consumption effects.

Kennedy *et al.* (2006) of the Australian Treasury estimate that a pandemic half as severe as that of 1918 would reduce Australian GDP by 9.3 per cent.

The New Zealand Treasury (2005) estimates that a severe pandemic could reduce GDP by 10 to 20 per cent in the year that the pandemic occurred and by 15 to 30 per cent over the medium term.

Using the CBO's mortality and morbidity assumptions, Jonung and Röger estimate an impact of –1.6 per cent on European Union GDP.

2 Approach of this Study

In "The Political Economy of Large Natural Disasters" Albala-Bertrand (1995)defines a natural disaster as one induced by a natural event interacting with a vulnerable social setting. Natural disasters include earthquakes, hurricanes and floods as well famines and mass epidemics. He divides the economic effects of a natural disaster into direct and indirect effects. Direct effects stem from the effects of the disaster on people, capital and the natural environment, while indirect effects stem from impacts on the way people and economic units relate to each other.

The direct effects of an influenza pandemic are the hours worked and production losses associated with death and illness, while indirect effects could include psychological impacts on demand for certain products, absenteeism stemming from fear of contracting the illness in the workplace and, if peak absenteeism is sufficiently high, production and supply chain disruptions.

In estimating these direct and indirect effects we seek wherever possible to ground our estimates empirically. A future pandemic will not be the first that humans will have experienced. A wealth of data exists to enable us to understand how past pandemics affected human health, human behaviour and the economy. While some studies reference the experience of SARS, no previous study that we are aware of examines in detail the actual economic impact of past pandemics. We closely examine these impacts in this study. Inferences regarding the impact of a prospective pandemic naturally require consideration of the relevance of economic and social changes since the previous pandemics. This we also do.

3 The Characteristics of Past Influenza Pandemics

There have been three influenza pandemics during the past 100 years – in 1918, 1957 and 1968. Morbidity rates (the proportion of the population experiencing symptoms) ranged between 20 and 35 per cent, and many more were likely infected but asymptomatic. While high infection rates were common to these three pandemics, resulting mortality differed greatly. The 1918 pandemic featured much higher mortality than the 1957 and 1968 pandemics. Case mortality rates in 1957 and 1968 did not differ much from those of normal winter epidemic influenza.

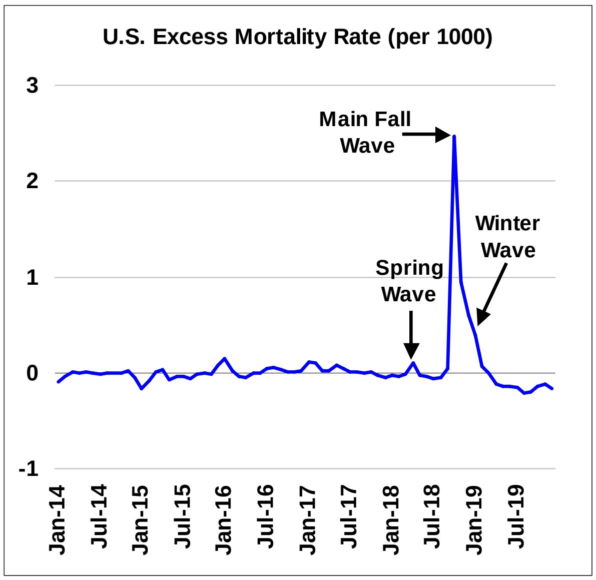
There is thus no generic pandemic, either in terms of mortality or economic consequences. A pandemic could be associated with high mortality as in 1918, or low mortality as in 1957 and 1968, or something different.

While past pandemics have featured several waves of morbidity, most cases have been concentrated in a single wave lasting no more than 6 to 8 weeks in any given location. This would likely be the only wave with any noticeable economic effects.

3.1 The 1918 Pandemic

The 1918 influenza pandemic was far more severe than any other for which we have reliable data. About 20-25 per cent of North Americans fell ill between September 1918 and January 1919. U.S. case mortality ranged between 1 ¾ and 2 ¼ per cent, with half the deaths occurring in the month of October (Figure 3.1).

Figure 3.1



Patterson and Pyle (1991) provide an excellent account of the geography of the 1918 pandemic. A mild "heralding wave" that attracted little attention at the time was first noted in the U.S. mid-west in March 1918. By May, it had spread to Western Europe, China and Japan, and by the summer to New Zealand, Australia and India. While the spring wave was first noted in the United States, the true geographic origin has not been well established. Before and after 1918, most influenza pandemics originated in Asia.

The much more lethal fall wave was highly contagious and spread very quickly, appearing first in Portugal and France in August, Western Europe and the East coast North American ports in early September and the West coast North American, South American, African, Indian and Asian ports in late September. By October, only New Zealand, Australia and the deep interior of South America, Africa and Asia were unaffected. By November, most of these had been struck. Australia was affected in January 1919 when a maritime quarantine failed. A third wave affected some locations in December 1918 and January 1919. Population mortality was considerably lower than in the main fall wave. Socially dense U.S. army and navy training bases appeared to have been unaffected by the third wave.

The relationship between the mild spring wave and the severe fall wave is obscure. Patterson and Pyle argue that "the most likely hypothesis is that the new strain emerged in early August by genetic mutation or recombination in western France." However, Taubenberger and Morens (2006) question whether the first and second waves were actually caused by the same virus. They note that three extensive pandemic waves occurring in one year was unprecedented and ask how susceptible persons could be "too few to sustain transmission at one point yet enough to start an explosive new wave a few weeks later?" They argue that the viral drift required should have taken years of global circulation rather than a few weeks of local circulation, and only positive human samples from all three waves will enable these questions to be answered (as yet, only the fall wave virus has been retrieved).

The prominent feature of the multiple waves in 1918-19 is that almost all the morbidity and mortality was associated with a single wave that spread globally with extraordinary rapidity. This wave was severe but of short duration, with about 80 per cent of cases occurring in a single month in a given location.

Total U.S. population mortality was 18.1 per 1000 in 1918, compared with an all-cause base mortality of 14 per 1000 in 1917, yielding excess mortality of 4.1 per 1000. Similar excess mortality effects are apparent in other advanced economies. The range of estimated global mortality impacts is very wide, ranging from 15 to 100 million. This corresponds to an excess mortality rate of 8.3 to 55.2 per 1000, reflecting a much higher estimated mortality in less developed countries. British India provides the best source of data, with official death registration data suggesting an excess mortality of 38 per 1000 in 1918. Davis (1951) concludes based on census data that this represents an underestimate and argues that the true number was 48 per 1000. Little is known about mortality in most other less-developed countries. High global estimates tend to assume that mortality in much of Asia and Africa was similar to that estimated for India.

In the 1910s people were much more likely to die of influenza and pneumonia in a non-pandemic year than is the case today. Age-adjusted U.S. mortality from influenza and pneumonia was 267 per 100,000 in 1917 compared with 35 in 1998. This reflects the fact that improved population health and better medical care have led to large reductions in base pneumonia mortality.

Mortality in 1918 was unusually great in the 20-to-40 age group (figure 3.2) with males disproportionately affected. The impact on the labour force would thus have been greater than in standard influenza epidemics that disproportionately affect the very young and the very old. The mortality spike at age 35 did not reflect a higher attack rate, but rather a spike in pneumonia as a secondary complication (figure 3.3).

Figure 3.2

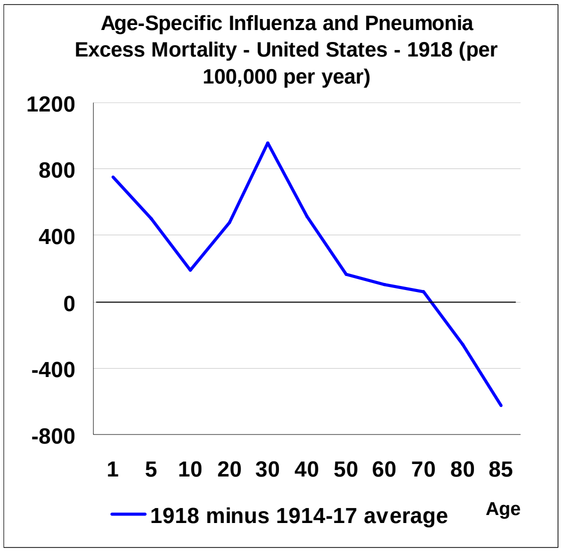
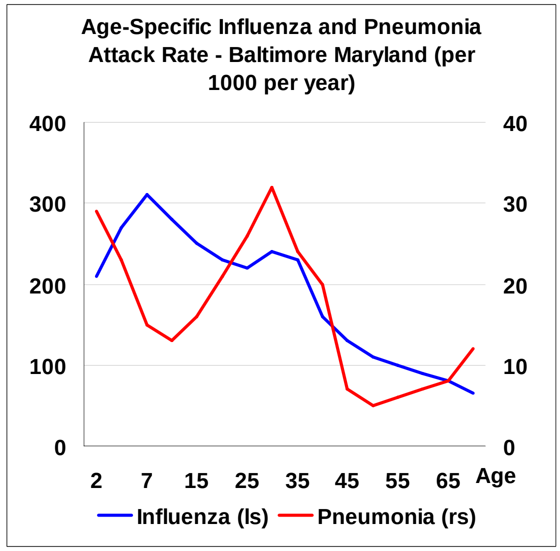


Figure 3.3



Secondary pneumonia, rather than influenza itself, was the chief killer in 1918. As *The Report of the Secretary of the Navy* (1919) states:

> Of the cases of influenza in which complications did not develop--800 to 875 in a thousand … were ordinary cases of influenza, similar to the grippe cases of ordinary times. In some of the uncomplicated cases, the patient appeared to be very ill for three or four days. On the other hand, there were always numerous mild attacks which either did not prevent the performance of usual tasks or necessitated confinement to bed or quarters for only one, two, or three days. The frequency with which very mild cases were seen leads to the belief that a great many persons were attacked by the disease in such mild form that it was not recognized even as an acute minor respiratory affection. The outstanding feature of the pandemic was the frequency with which secondary pneumonia of the bronchial type developed. As a rule, from 100 to 200 cases in a thousand had pneumonia complications with definite clinical manifestations. The causes of death other than pneumonia were few.

Consistent with this, Kilbourne (2005) finds that in 1918 “most patients experienced symptoms of a typical influenza with a 3-5 day fever followed by complete recovery.” Taubenberger and Morens note that “despite the extraordinary number of global deaths, most influenza cases in 1918 (more than 95% in most locales in industrialized nations) were mild and essentially indistinguishable from influenza cases today.”

Noymer and Garenne (2000) suggest that high pneumonia complication rates among males age 20-40 may have resulted from interactions between influenza and endemic tuberculosis that was more prevalent in this group. This is supported by the fact that tuberculosis death rates fell sharply after the pandemic, particularly among males, contributing to a sharp and long-lasting narrowing of male and female mortality rates.

Negative excess mortality among the elderly reflected a very low attack rate that may have stemmed from immunity derived from exposure to a similar but less lethal virus about 40 years earlier. However as Taubenberger and Morens note, this "would present an additional paradox: an obscure precursor virus that left no detectable trace today would have had to have appeared and disappeared before 1889 and then reappeared more than 3 decades later."

We estimate that the daily influenza morbidity rate peaked at 4 per cent in the United States in the third week of October 1918 (see Figure 3.4; for details on the reconstruction of morbidity rates see Annex A). For single cities, we estimate an average daily peak of 5 ½ per cent occurring about 3 weeks after the appearance of the first case. The City of Toronto reported influenza absenteeism rates in a number of departments of close to 6 per cent in mid-October 1918. For children and young adults the attack rate was close to 30 per cent, implying a morbidity peak of 8.1 per cent. This is very close to an actual peak excess absenteeism of 9 per cent reported by the Toronto public school system (see Table 3.1). We estimate that morbidity then fell quickly to about 0.7 per cent 3 weeks later. A sharper and more compressed morbidity distribution is apparent at the socially dense U.S. naval training station at Great Lakes Illinois, where we estimate that daily morbidity peaked at about 11 per cent a mere 12 days after the first case, and then fell sharply.

Figure 3.4

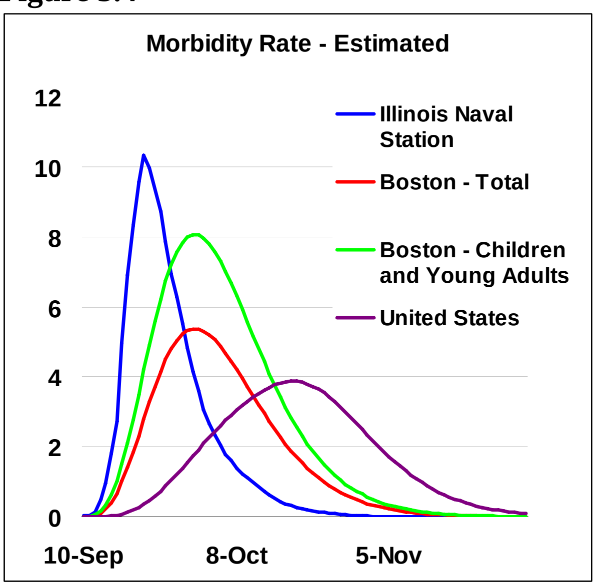


Table 3.1 Student Absenteeism Rate – Toronto Public School System

	Absent	Per Cent
October 1917	7260	11.0
October 11, 1918	13172	20.0
Excess	5912	9.0

3.2 The 1957 and 1968 Pandemics

The 1957 pandemic virus was first identified in East Asia in February 1957. Vaccine production began in May, with limited supplies available in North America by August. Sporadic cases appeared in North America in June, however, the pandemic began in earnest at the beginning of September, with the bulk of morbidity and mortality concentrated in the month of October. A second wave with much lower morbidity began in December even before the first wave had fully run its course. The second wave tailed off in February 1958. As in 1918, most of the impact occurred in one wave, and within that wave, most occurred in a single month.

The North American attack rate in 1957 was around 35 per cent with a case mortality rate of 0.12 percent implying population mortality of 0.4 per 1000. Mortality was concentrated among the very young and very old. Morbidity rates were highest among persons under age 20 (see Monto (1987)). Global population mortality is estimated to have been about 0.7 per 1000.

The 1968 pandemic was milder than that of 1957. The main wave struck in December 1968 with U.S. population mortality at just under 0.2 per 1000 and global mortality at around 0.3 per 1000.

4 The Economic Impacts of Past Pandemics and of SARS

4.1 The Economic Impact of the 1918 Pandemic

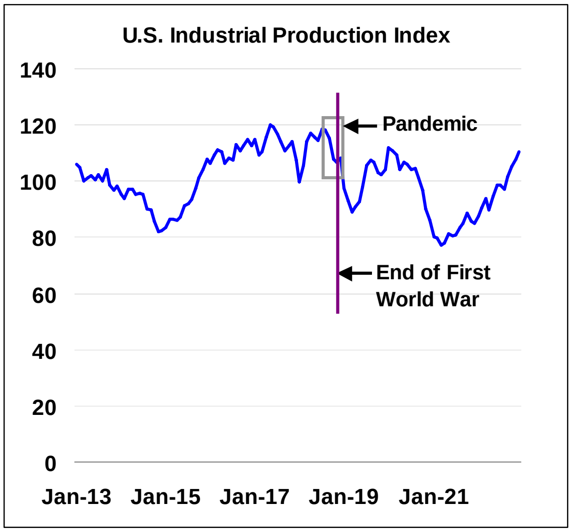
While official BEA GDP estimates do not exist prior to 1929, the NBER Macro History Database provides a rich source of high frequency data to analyze the economic impact of the 1918 pandemic. Monthly data for the production of a wide variety of commodities is available, as well as goods trade data, data on the consumption of travel services, retail sales, equity prices and currency demand. Analysis of the effects of the pandemic requires the use of monthly data, as the pandemic was highly concentrated in the single month of October. If the pandemic had notable effects on the economy, then these effects should be apparent in that month, with rebounds occurring in subsequent months.

Monthly data on industrial production is a key source of information on the aggregate impact of the pandemic. To translate this into GNP impacts we regress the annual growth of the Romer (1988) real GNP series on annual growth of the NBER index of industrial production and trade. Results are reported in Table D.4 of Annex D and indicate that a 1 per cent change in this index was associated with a 0.26 per cent change in GNP.

Figure 4.1 provides monthly levels of the NBER industrial production index. The pandemic main wave was limited to the September-November period with half the morbidity occurring in October. During the fall wave, industrial production averaged 7 per cent below the August level. This translates into a –1.7 per cent annual impact and a –0.45 per cent GNP impact using the estimated GNP-industrial production elasticity. This may be an overestimate as the First World War ended in November and part of the

November weakness likely reflects the cancellation of defence orders. The decline during the fall wave is considerably smaller than declines during normal business cycle contractions of the period.

Figure 4.1



In the first decades of the 20th century, the Pullman Company kept detailed data on passenger miles carried, while the City of New York recorded all passenger trips on its subways and street railways. This data, along with monthly retail sales data allows us to gauge the indirect effects of the pandemic on sectors that could have been vulnerable to psychologically-induced demand reductions. Figures 4.2 and 4.3 provide this information relative to the averages of the previous years to control for seasonal effects.

Pullman rail passenger traffic shows no apparent impact of the pandemic. Traffic was unchanged in September 1918 and actually rose in October, the peak month of the fall wave. A possible pandemic impact is apparent in New York transit use, which rose in September, then fell in October, before recovering in November. The annual impact is small, however, amounting to only –0.6 per cent. A *New York Times* article from October 25 1918 reported that “the effect of the epidemic is seen more in the spreading of travel over more hours than in the diversion of travel.” Retail sales also declined somewhat during the pandemic months although the decline in October is smaller than the standard deviation of monthly changes in the series. The implied annual impact is –1.4 per cent. On balance, the apparent impact of the 1918 pandemic on sensitive sectors ranges between indiscernible and modest.

Figure 4.2

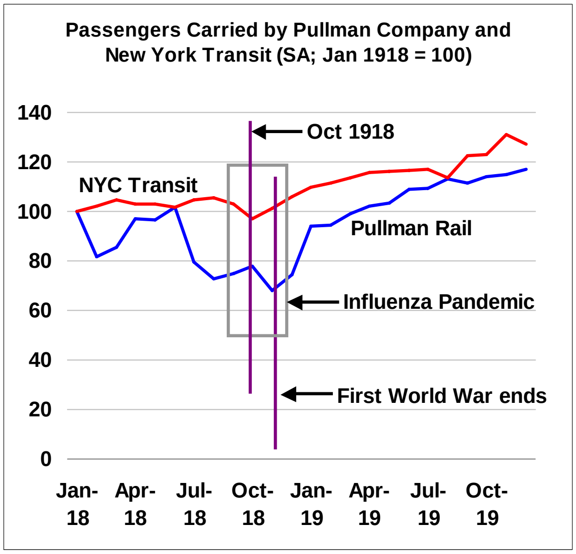
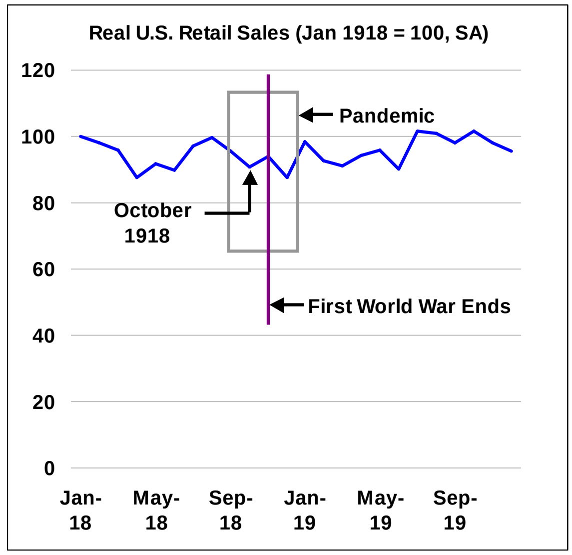


Figure 4.3



Some argue that a pandemic would disrupt trade flows. However, as Figure 4.4 shows, no such impacts were apparent in 1918. While real imports declined modestly during the peak pandemic months, the decline is very small relative to the typical volatility of the series. Real exports were effectively stable.

Kennedy *et al.* and the IMF Working Group suggest that a pandemic could negatively affect equity markets and induce people to hoard cash. Again, no such effects were apparent in 1918 (Figures 4.6 and 4.7). The Dow-Jones Industrial average was flat during the pandemic while railroad stocks actually increased in value. Some have argued that a pandemic would lead people to hoard cash, however, real currency holdings by the public actually fell modestly during the 1918 fall wave. In 1918, Americans would have had much greater reason to be nervous about the solvency of their local bank in the event of a negative shock than would be the case today, as bank failures were frequent in the United States prior to the introduction of Federal Deposit Insurance in 1934 and tended to surge during economic downturns.

Figure 4.4

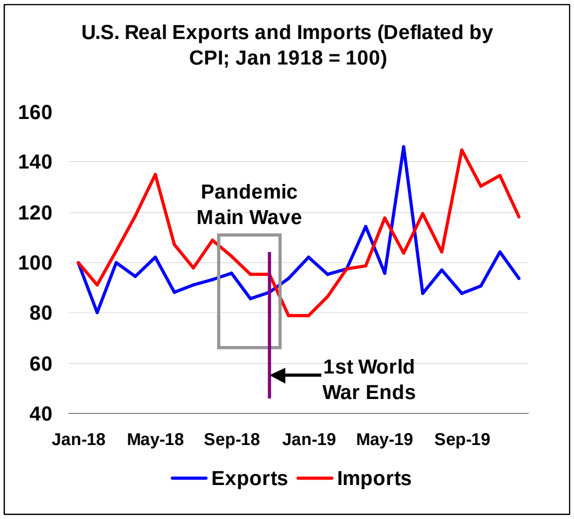
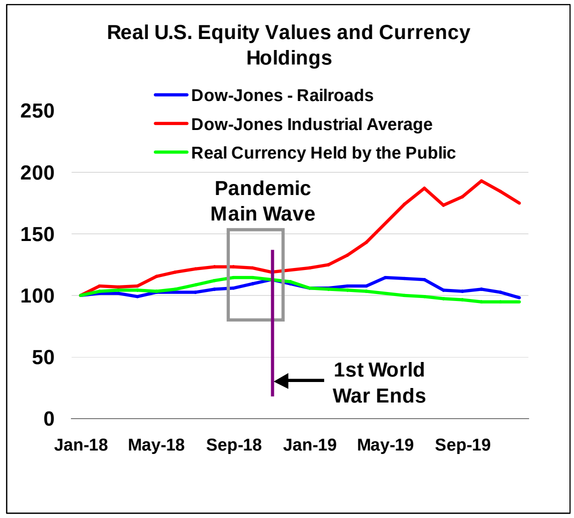


Figure 4.5



There is no evidence of any absenteeism-related disruption in the financial sector, as daily bank clearings actually rose (figure 4.6). Bankruptcy data show no evidence of any pandemic impact on the financial health of the manufacturing sector.

Figure 4.6

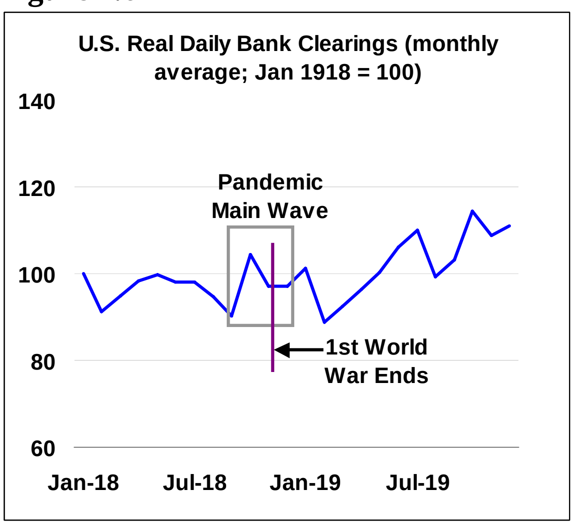
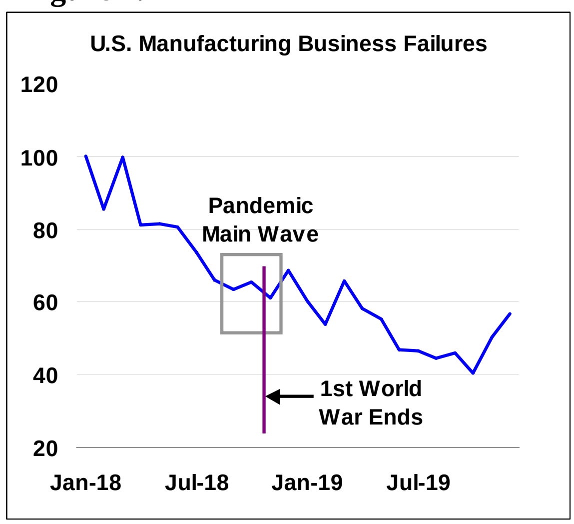


Figure 4.7



Media coverage of the period conveys a picture that accords qualitatively with the data. The most striking aspect of the coverage of the economic impact of the pandemic is how little there was. Of the 84 pandemic-related articles published in the *Toronto Star* between September 23 and October 26 1918, only 9 dealt with economic matters, and most of these provided qualitative reports on absenteeism.

An exhaustive search of the *Toronto Star*, the *Globe* and the *New York Times* reveals some evidence of brief retail demand and production impacts. *New York Times* articles from October 12 reported that sales of women's apparel had fallen sharply and that consumption expenditures had grown more conservative. However, on October 18 the

New York Times reported that "while…retail business has slowed down somewhat here as a result of the Liberty Loan and the influenza, the slump is said to be less marked than is generally thought." The article explained that "the epidemic is given its full share of the responsibility for keeping people out of the stores, but this handicap has been offset to quite some extent by the increase in telephone and local mail orders, especially the latter." The *New York Times* noted the absence of any impact on the clearing system on October 12. Articles reported reductions in textile and shoe production in New England (*New York Times* October 12), in the loading of coffee on steamships in Rio de Janeiro (*New York Times* October 28) and in mining output in South Africa (*Toronto Star* October 8). The *New York Times* reported large rebounds in retail sales on October 29 and in sales of women's apparel in articles published on November 17 and 22.

Overall, the data suggest that the 1918 pandemic had modest direct effects stemming from illness absenteeism, but that indirect effects were very small. This is consistent with the generalized finding of Albala-Bertrand that human activity is very resilient to many natural shocks. People adapt and work around the shock; those unaffected work harder and longer to pick up the slack. The short duration of the shocks also limits their impact. As Crosby (2003) says:

> …Spanish Influenza moved too fast to produce more than brief paralysis. It was a hit-and-run kind of disease, not the kind that places society under a long siege, like tuberculosis or malaria. Influenza does not create the kind of situation which is bound to get worse and worse unless proper actions are taken. (p.115)

4.2 The Economic Impacts of the 1957 and 1968 Pandemics

The Labour Force Survey of Canada's Dominion Bureau of Statistics recorded monthly illness absenteeism rates throughout the 1950s. Figure 4.8 provides monthly excess illness absenteeism rates for the years 1955 to 1958. These are calculated as the difference between each month's illness absenteeism rate and the average rate for that month over the years 1955, 1956, 1958 and 1959. The pandemic appears very clearly as a sharp spike in illness absenteeism in the fall of 1957. Excess illness absenteeism rose to 0.7 per cent in September, 3.1 per cent in the peak month of October, and then fell back to 1.1 per cent in November, 0.4 per cent in December and January and 0.2 per cent in February. Two distinct waves struck during this period; a main wave lasting from September to November, and a secondary wave from December to February. Calibration of our dynamic morbidity model to the monthly data yields an estimate that daily excess illness absenteeism peaked at 3.8 per cent in Canada around the 15^{th} of October (see Figure 4.9 and Annex B for details).

Figure 4.8

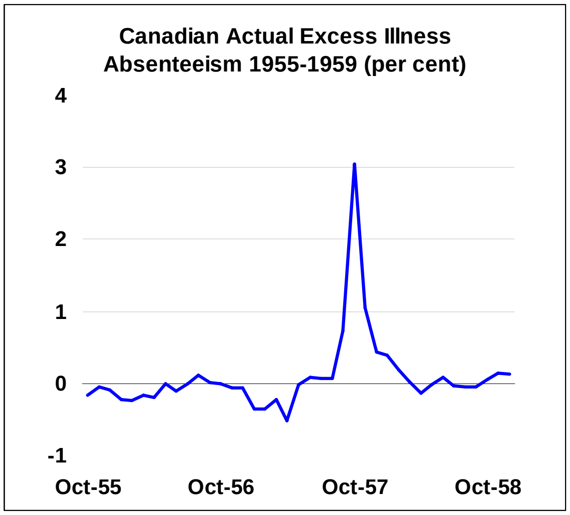
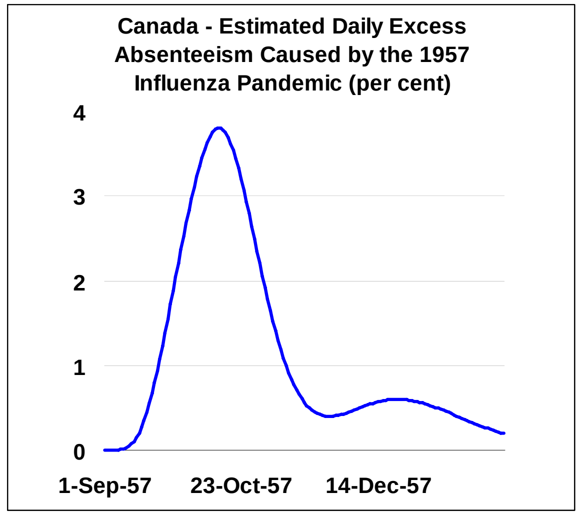


Figure 4.9



Canada and the United States suffered a capital investment recession that began in the late summer of 1957 and ended in the spring of 1958. This recession was preceded by a period of monetary tightening and equity market weakness and was accurately predicted by leading indicators. The recession was characterized by a sharp capital goods inventory cycle.

As in 1918, one must examine monthly data for any signs of economic impact of the pandemic. Figure 4.10 shows monthly growth of Canadian industrial production and the inverted monthly change in the excess illness absenteeism rate. Industrial production fell 1.9 per cent in September 1957, just as the pandemic wave began, with excess absenteeism rising by 0.7 percentage points. Industrial production fell by a smaller 1.1 per cent in October and excess absenteeism surged by 2.3 percentage points. In November, industrial production rose by 0.2 per cent and excess absenteeism fell by 2 percentage points.

To try to extract the pandemic signal from the underlying cycle we construct a filtered industrial production series consisting of a 5 month centred moving average that excludes October 1957 from the averaging, so as to avoid contamination of the trend with the peak pandemic effect (see Figure 4.11). Industrial production was 0.7 per cent below trend in September 1957, 1.2 per cent below in October, and at trend in November. If we take these as the actual pandemic impacts on industrial production, then this implies an annual impact of –0.15 per cent. We estimate that the elasticity of real Canadian GDP growth to industrial production growth was 0.58 during the 1950s, yielding an annual GDP impact of –0.08 per cent.

Figure 4.10

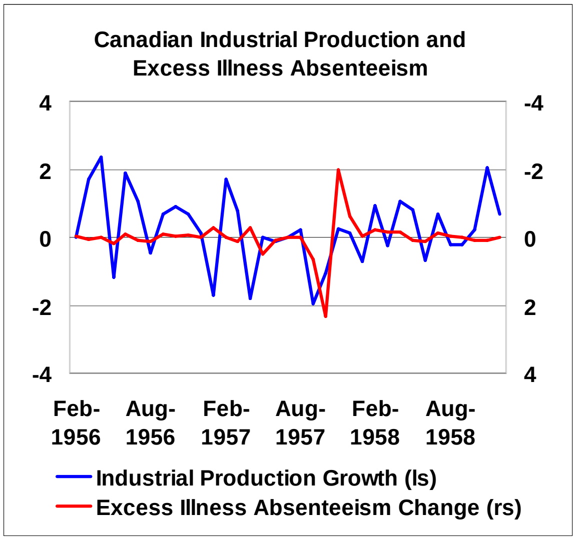
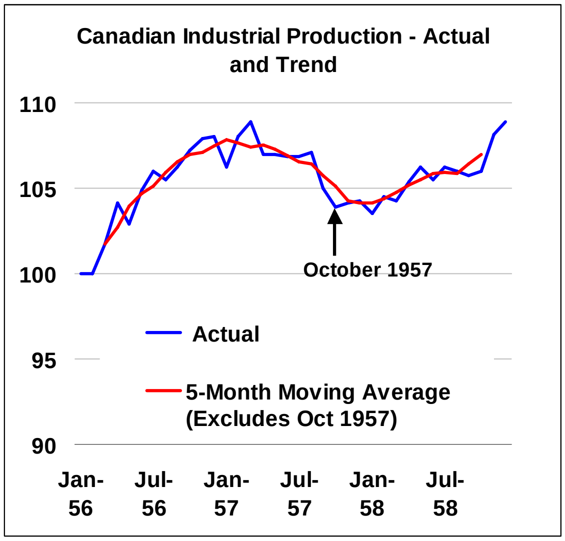


Figure 4.11



No pandemic impacts are apparent in Canadian monthly retail sales (Figure 4.12). Figure 4.13 shows the U.S. personal savings rate over the period 1956-69. Any pandemic impacts should appear as a noticeable spike in the pandemic quarter, however the savings rate actually fell in the fourth quarter of 1957 and was flat in the fourth quarter of 1968. In Canada, even absenteeism rates were unaffected by the 1968 pandemic.

Overall, the picture that emerges from the 1957 and 1968 pandemics is of possible very small direct economic impacts and no indirect impacts.

Figure 4.12

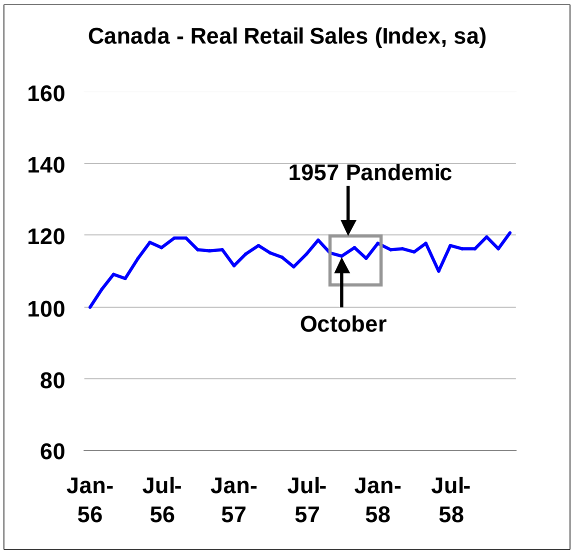
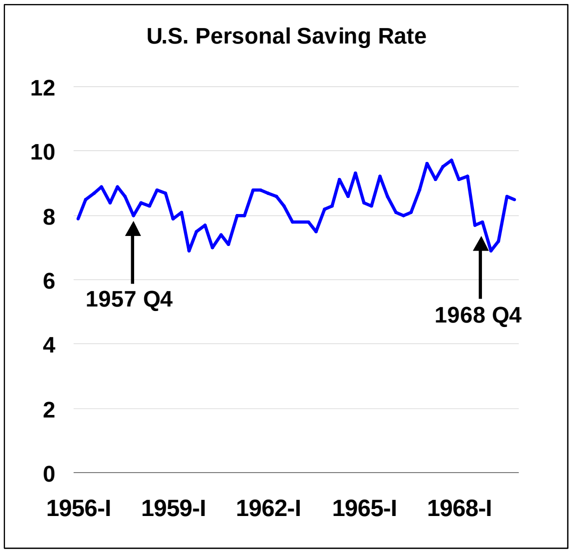


Figure 4.13



4.3 The Economic Impact of SARS

SARS was an atypical pneumonia that first appeared in China in late 2002. The disease reached Hong Kong and Vietnam in February 2003, and then spread to other countries in the spring. The WHO estimates that 8096 people were infected, of whom 774 died, implying a case mortality rate of 9.6 per cent. This compares with more than 10 million cases and 40,000 deaths from influenza globally in an average non-pandemic year. Canada was the most affected non-Asian country with 251 cases and 43 deaths, most of these in Toronto.

SARS did not transmit well in the broader community making it a candidate for containment strategies, such as quarantines, travel advisories and the screening of airline passengers for symptoms. About 3500 people were quarantined in Hong Kong, Singapore and Taiwan, and many more in Canada. Schools were closed in Hong Kong and Singapore. The WHO recommended the screening of airline passengers and advised against all but essential travel to Toronto.

Hong Kong – at the epicentre of SARS – suffered a real GDP decline in the second quarter of 2003, however this barely stands out relative to the typical volatility of Hong Kong GDP (Figure 4.14). This decline is fully explained by a fall in service exports (likely travel services) (Figure 4.15). Annual tourist visits equal 203 per cent of Hong Kong's population compared with 4 per cent for an economy like Japan, making total Hong Kong GDP much more vulnerable to reductions in visits from abroad. Service exports rebounded in the subsequent quarter while goods exports were unaffected. Air cargo shipments continued unabated even as personal air travel fell sharply.

Figure 4.14

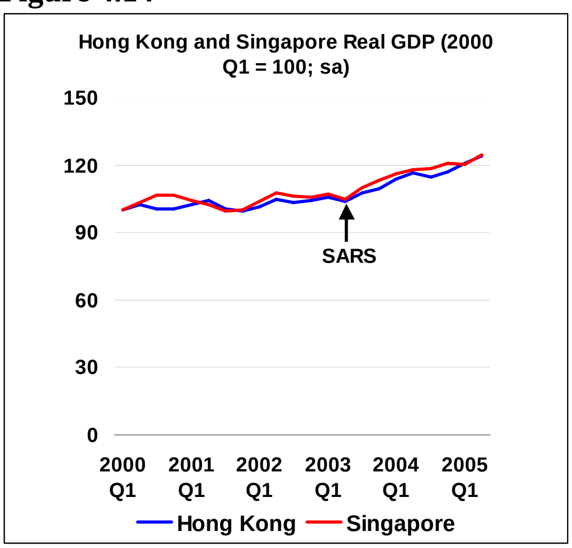


Figure 4.15

Restaurant revenues dipped a surprisingly small 10 per cent in the quarter (Figure 4.16), likely partly a result of reduced travel to Hong Kong. Hong Kong retail sales actually rose as SARS cases surged in March 2003 (Figure 4.17), at odds with McKibbin and Lee's (2003) assumption of a 15 per cent decline lasting six months. Siu and Wong

(2004) find that the Hong Kong economy "did not experience a supply shock, as the manufacturing base in the Pearl River Delta was unaffected, and goods continued to be exported through Hong Kong normally." They add that "initial alarmist reports about the negative economic impacts were not borne out." (p. 227).

Figure 4.16

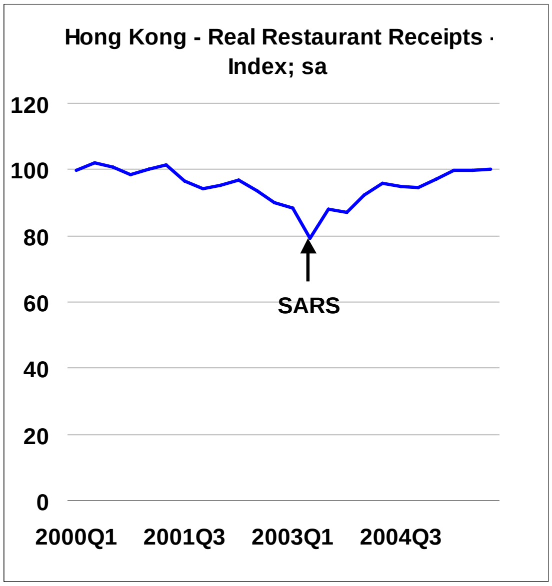
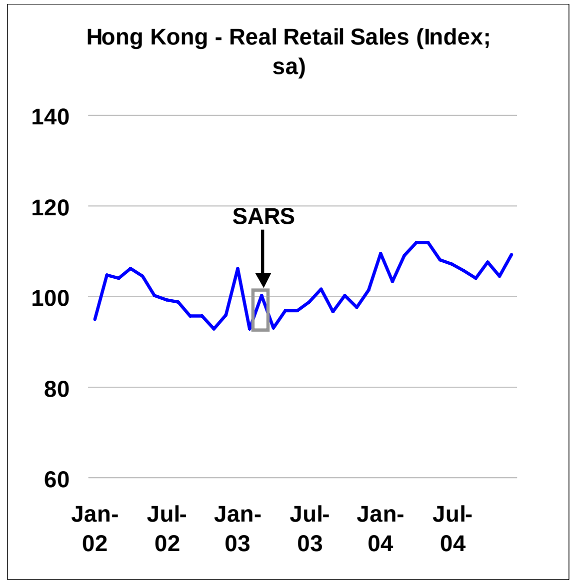
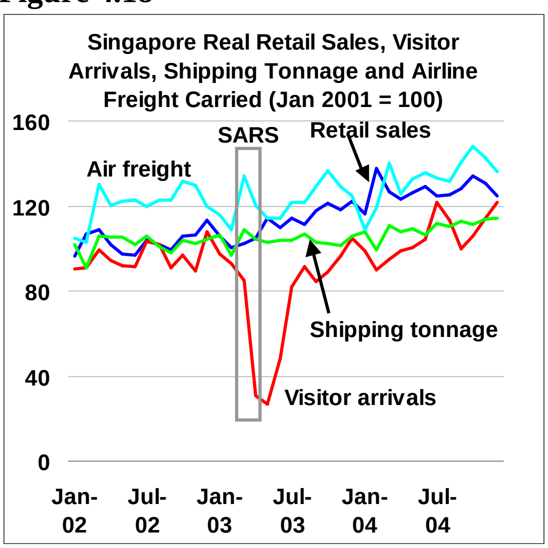


Figure 4.17



SARS struck Singapore in March and April of 2003. Visits plunged in April and remained depressed in May, before beginning a sharp rebound in June (see Figure 4.18). Hotel occupancy fell from 71 per cent in March to 34 per cent in April. The quarterly GDP pattern is similar to that of Hong Kong. As in Hong Kong, retail sales were completely unaffected, and shipping tonnage and freight carried by Singapore Airlines actually rose during the height of SARS.

Figure 4.18



SARS impacts are not apparent in the annual growth patterns of Hong King, China and Vietnam (Table 4.1). All three economies experienced faster growth in 2003 than in 2002. Only in Singapore did annual growth slow in 2003.

Table 4.1: Real GDP Growth – Asian Countries Affected by SARS

	Hong Kong	China	Singapore	Vietnam
2000	10.2	8.0	9.6	6.8
2001	0.5	7.5	-2.0	6.9
2002	1.9	8.3	3.2	7.1
2003	3.2	9.5	1.4	7.3
2004	8.1	9.5	8.4	7.7

Real GDP declined in Canada in the second quarter of 2003. Newcomb (2005) has cited this as evidence that SARS had a significant negative impact on the Canadian economy. A deeper analysis of the data does not support this conclusion.

Real net exports of travel services declined in the SARS quarter and have remained well below pre-SARS levels since then (Figure 4.19). At first glance, this seems to support the idea of a significant and even long-lasting impact. However, this apparent correlation is deceptive as it ignores the role played by the unprecedented appreciation of the Canadian dollar against the U.S. dollar in the second quarter of 2003 (Figure 4.20). This appreciation fully explains the decline in net exports of travel services, with the residual from a regression of net exports of travel services on the real Canada-U.S. exchange rate showing no role for SARS (see Appendix D for econometric details).

Figure 4.19

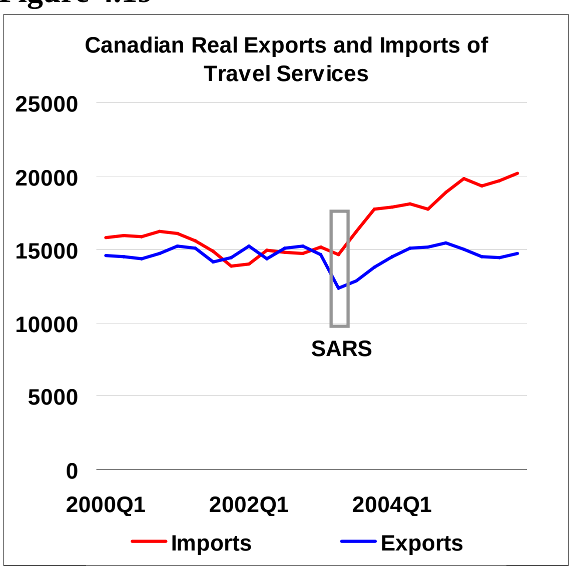


Figure 4.20

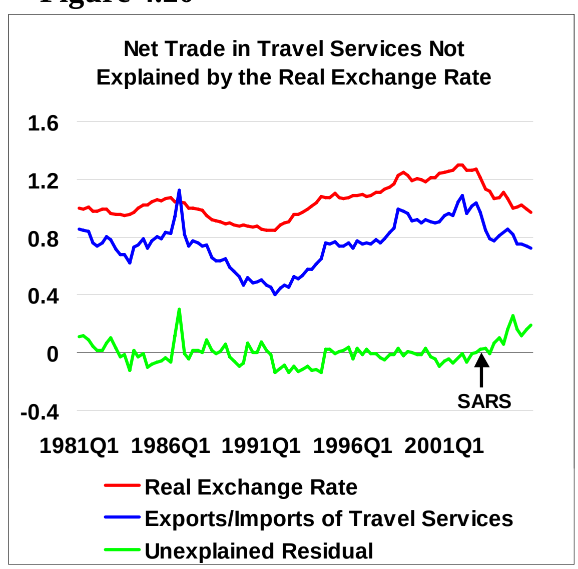


Figure 4.21 shows that SARS had no apparent impact on the output of either the transit and ground transport industry or the food service and drinking place industry. In Ontario – dominated by Toronto, the city most affected by SARS – retail sales and restaurant receipts actually grew faster during the outbreak than in the rest of Canada (Figure 4.22). While anecdotal reports at the time suggested that these sectors were significantly

affected by SARS, the hard data do not support this. Some individual firms may have been affected, but not enough to show up in the aggregate data.

Figure 4.21

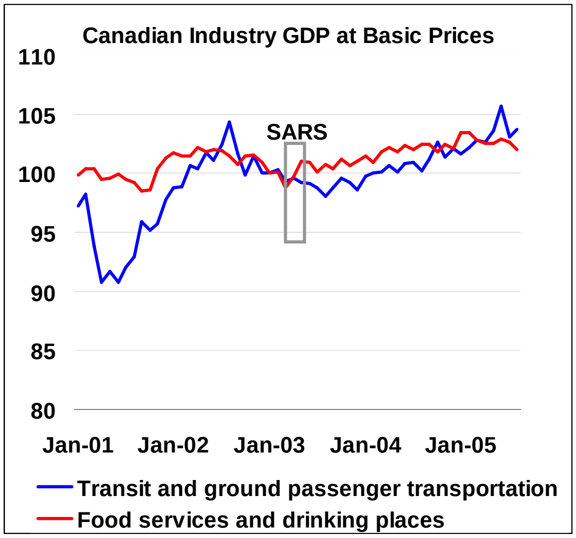
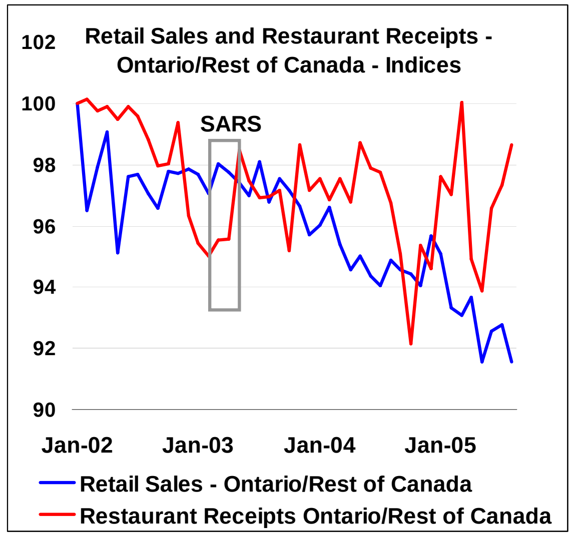


Figure 4.22



The output of the air transportation industry fell 14 per cent between March and May 2003, while accommodation output fell 8 per cent (Figure 4.23), with the accommodation decline likely resulting from reduced travel. Much of this doubtless reflected fear by international travelers of flying to Toronto during the outbreak, however, a significant portion may have been unrelated to SARS. The SARS outbreak coincided with start of the second Gulf War and heightened fears of terrorist attacks. As Figure 4.24 shows, U.S. global air travel declined sharply at the time of the first Gulf War. Similar impacts are apparent when the second Gulf War began, with travel to Atlantic and Pacific destinations affected equally. This suggests that most of the decline in U.S. international travel in the spring of 2003 reflected a generalized fear of terrorism, not SARS. If SARS had been the principal cause then we would have expected to see a much greater impact on travel to Pacific destinations than to Atlantic destinations. In the case of travel to Canada we cannot easily disentangle SARS from heightened fear of terrorism, and it is likely that both played a role in the reduction in air travel during this period.

The reduction in Canadian travel services and accommodation output between March and May equals 0.03% of 2003 GDP. While much of this may have stemmed from SARS, some likely reflected a generalized fear of international air travel at the time of the second Gulf War.

Figure 4.23

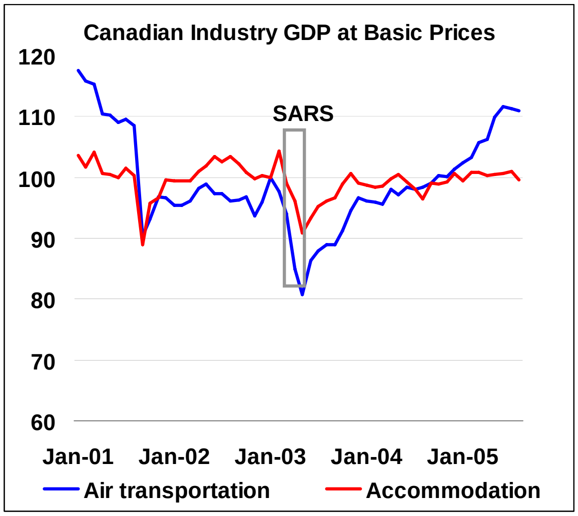
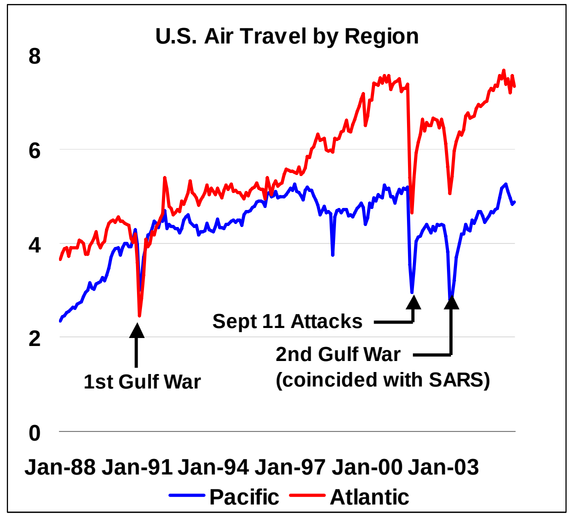


Figure 4.24



Some studies assume that an influenza pandemic would have large negative indirect effects based on the experience of SARS. Bloom, de Wit and Carangel-San Jose (2005) argue that "the outbreak of SARS in 2003 showed that even a disease with a relatively small health impact can have a major economic impact." Fan (2003) says that the "pronounced impact of SARS" can be attributed to "the almost costless and rapid transmission of information due to the development of modern media and communications technologies." McKibbin and Sidorenko develop assumptions regarding the psychological effects of an influenza pandemic using a framework that is identical to that developed by McKibbin and Lee in their analysis of SARS. McKibbin and Lee express the essence of this framework as:

> First, fear of SARS infection leads to a substantial decline in consumer demand, especially for travel and retail sales service. The fast speed of contagion makes people avoid social interaction. The adverse demand shock becomes more substantial in the regions which have much larger service related activities and higher population densities, such as Hong Kong or Beijing, China. The psychological shock ripples all around the world … since the world is so closely linked by international travel. Second, the uncertain features of the disease reduces confidence in the future of the affected economies…the loss of foreign investors' confidence would potentially have tremendous impacts on foreign investment flows. (p.4)

Our reading of the evidence leads us to quite different conclusions regarding the lessons of SARS. The hard data suggest that SARS had one economic impact – namely, a temporary reduction in international travel to affected locations, with some associated impacts on accommodation. No other impacts are apparent in either South Asia or Canada. Goods trade, supply chains and retail sales were all unaffected.

We do not know what the state of mind was of people living in locations affected by SARS. Survey data from Taiwan suggests that they were fearful and uneasy – just as people in 1918 likely were on a much greater scale. Nevertheless, their behaviour did not change in ways that led to observable economic impacts.

McKibbin and Sidorenko argue that "the fear of an unknown deadly virus is similar in its psychological effects to the reaction to bio- and other terrorism threats." We have no data to refute or support this, however, we would agree that the behavioural effects of an event like the September 11th terrorist attacks resemble those of SARS. U.S. passenger transportation dropped sharply in the wake of September 11th (Figure 4.25). Not surprisingly, air passenger transportation was particularly hit, but personal vehicle transportation across the Canada-U.S. land border also dropped noticeably. However, freight transportation was essentially unaffected. Even airfreight transportation suffered a surprisingly small decline given that air traffic was actually halted for a period after the attacks.

U.S. retail sales dropped slightly in September 2001 and automobile sales fell modestly (Figure 4.26). This may or may not have been because people felt uneasy or depressed following the attacks. However, as Albala-Bertrand stresses, people operating in market economies are not passive in the face of disasters. Automobile dealers responded to the perceived demand weakness by offering zero per cent financing of new purchases. This led to a close to 25 per cent surge in automobile sales in October that dwarfed the September decline. At the time of September 11th many feared a blow to consumer confidence that would tip the United States back into a protracted recession. The data suggest that the market response to the attacks ensured that actual effect on cumulative retail sales over the September-December period was positive rather than negative.

The behavioural responses to SARS and September 11th share a common feature. In both cases, people temporarily avoided air travel as risk-reduction strategy. In the case of SARS, they avoided travelling to the locus of infection. After September 11th they avoided a mode of travel that they suddenly perceived as riskier. However, what they did not do is as interesting as what they did do. Those who actually lived in Hong Kong, Singapore, Taiwan and Toronto did not "hunker down" or flee in panic. Rather, they carried on with their lives, including working and shopping. They may have been anxious – 50 per cent of Taiwan respondents reported wearing a mask during the height of SARS – but they did not become paralysed with fear, even in the face of intense media coverage.

The difference between international travellers and the residents of the affected locations is that the former could easily avoid the perceived risk, whereas the latter could not. A risk that is pervasive and hard to avoid engenders coping strategies that enable people to continue functioning. These strategies involve selective processing of information that reduces the disutility associated with anxiety regarding the risk. Their importance is stressed in an emerging literature that merges insights from psychology and economics (see, for example, Slemrod, 2003). When a risk is pervasive, the relative risk associated with particular activities will also tend to shrink.

Figure 4.25

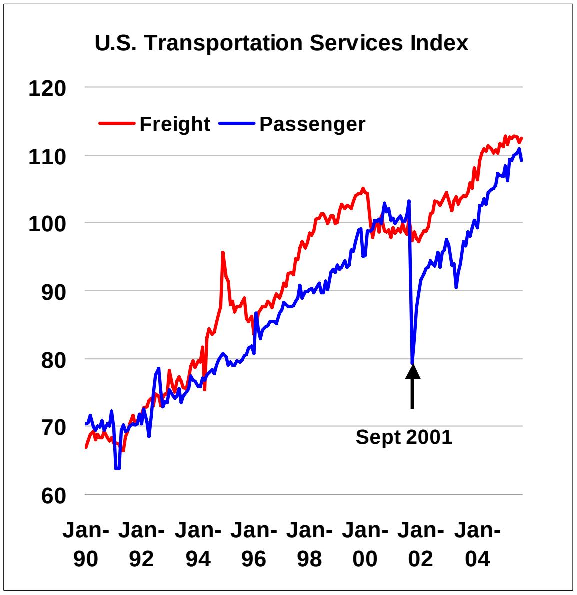
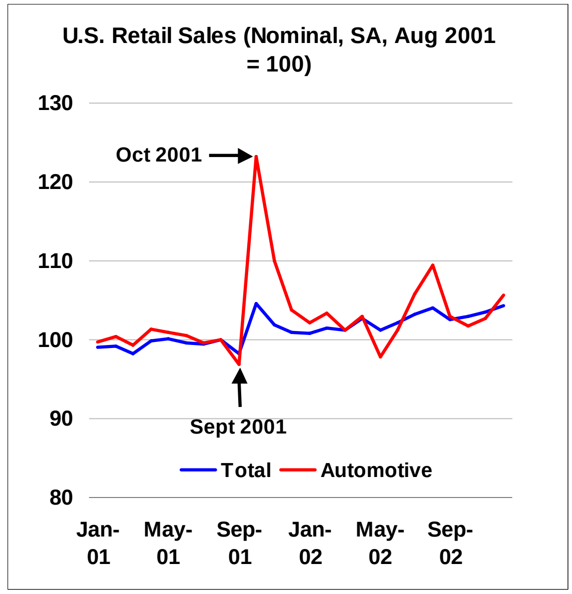


Figure 4.26



5 Assessing the Relevance of Economic and Social Changes Since 1918

In the fall of 1918, the most severe influenza pandemic ever recorded quickly spread across the entire globe. Severe though the effects on human health were, it appears to have had only minor impacts on the world's most advanced economy – that of the United States. Indirect effects are hard to discern, in the United States or elsewhere.

Both economies and societies have evidently changed considerably since 1918. In most advanced economies, agriculture is much less important, and services more important than in 1918. Many countries were at war in 1918. Social safety nets were much less extensive and the role of government in the economy smaller. Many fewer married women were in the labour force, although the war boosted female participation.

While much has changed since 1918, many changes are of degree rather than kind. Advanced economies of today have more in common with the United States of 1918 than the latter had with the pre-industrial agrarian America of 1818. The United States in 1918 had an advanced capitalist economy with well-developed financial markets that was highly integrated with the rest of the world economy through both trade and financial channels. Global business cycles were closely aligned, the Great Depression of the 1930s being the most prominent example. The Internet may not have existed, but news and financial market information were quickly transmitted globally via transoceanic telegraph and telephone cable. Television did not exist, but the advanced nations of 1918 had already entered the era of mass communications. Most major cities had several daily newspapers, and these had high circulations.

A new literature has begun to explore the coping strategies that people adopt in situations of stress and risk, and their implications for economic behaviour. It seems unlikely that these strategies have changed since 1918. The question remains whether the economic and social changes that have occurred are of a type that could transform the very small observed economic impact of the 1918 pandemic into the much larger (and even catastrophic) impacts predicted by some analysts.

The U.S. labour share of income has changed little since 1929, suggesting little change in the aggregate elasticity of output with respect to hours worked. Direct effects should therefore be similar to those of 1918 for a pandemic of comparable severity. Most of those who predict that a future pandemic would have a large negative impact do so on the basis of large indirect effects. The factors that might potentially lead a new pandemic of comparable severity to have a different indirect effects than that of 1918 are as follows:

1) Changes in the mix of occupations and of output
2) The First World War
3) Changes in the production process
4) Changes in the availability of leave
5) Changes in mass communications

5.1 Changes in the Mix of Occupations and of Output

In 1910, agricultural occupations accounted for 32 per cent of all occupations in the United States, compared with 0.3 per cent in 2004. Industrial production occupations decreased in importance from 22.5 per cent in 1910 to 8 per cent in 2004. The share of occupations in construction and extraction has also declined. The occupation share of business and financial operations is very similar today to that of 1910. Notable increases in occupation share have occurred in education, health, sales and office and administrative support. The occupation share of transportation has increased only modestly.

Some argue that a pandemic today would cause widespread workplace-avoidance absenteeism in socially dense occupations. Determining which occupations are socially dense involves considerable judgement. We define low social density occupations as those where much of the working day would likely involve limited direct physical interaction with others, or where the primary place of work is out of doors. Occupations that involve dealing with the public may or may not be more socially dense than those that do not. A real estate agent, for example, may be exposed to many fewer people each day than someone working in a closed factory setting.

We identify low social density occupations in Annex E. We estimate that 48 per cent of U.S. occupations featured low social density in 1910, compared with 28 per cent in 2004 (see Table 5.1). Much of the difference reflects the reduced importance of agricultural occupations. We estimate that 28 per cent of Canadian occupations can also be classified as low social density in 2005. The remaining 72 per cent of occupations should not be thought of as of uniform high social density, rather, they feature a continuum of social densities ranging from low to high.

Table 5.1: Composition of U.S. Occupations – 1910 and 2004

Code	Occupation	1910%	2004%
11-0000	Management	18.9	4.7
	Management - excluding farm	2.8	4.7
13-0000	Business and financial operations	4.5	4.1
15-0000	Computer and mathematical	0.0	2.3
17-0000	Architecture and engineering	1.2	1.8
19-0000	Life, physical, and social science	0.2	0.9
21-0000	Community and social services	0.4	1.3
23-0000	Legal	0.3	0.8
25-0000	Education, training, and library	1.6	6.2
27-0000	Arts, design, entertainment, sports, and media	0.7	1.3
29-0000	Healthcare practitioners and technical	1.1	5.0
31-0000	Healthcare support	0.0	2.6
33-0000	Protective service	0.6	2.4
35-0000	Food preparation and serving related	5.0	8.2
37-0000	Building and grounds cleaning and maintenance	0.9	3.3
39-0000	Personal care and service	1.5	2.4
41-0000	Sales and related	4.0	10.6
43-0000	Office and administrative support	4.7	17.5
45-0000	Farming, fishing, and forestry	15.7	0.3
47-0000	Construction and extraction	9.6	4.9
49-0000	Installation, maintenance, and repair	1.6	4.1
51-0000	Production	22.5	7.9
53-0000	Transportation and material moving	5.2	7.4
	Low Social Density	**48.4**	**27.5**
	Physically Strenuous	**74.2**	**32.9**

While the average social density of occupations has clearly increased since 1918, this cannot in itself explain the small economic impacts of the 1918 pandemic, as there is no evidence that higher density industries suffered disruption in 1918. As we have seen, pandemic impacts were small or indiscernible in retail services, rail and transit passenger transportation and banking. This suggests that workplace avoidance absenteeism was small even in socially dense occupations in 1918. Had workplace avoidance absenteeism occurred in socially-dense occupations in 1918, it would have affected the total economy less than today, however, there is no evidence that it did affect these occupations. Whether workplace avoidance absenteeism would be more likely to occur today is a separate issue to which we will return in Section 6.3.

A much higher proportion of U.S. occupations were physically strenuous in 1910 than in 2005, likely implying a longer period of physical incapacity to perform a job for a given period of illness and recuperation.

Changes in the industry composition of Canadian GDP mirror to some degree the changes in U.S. occupations (see Table 5.2). The output share of agriculture, forestry and fishing is now about one-tenth of its 1926 level, while finance, insurance, real estate and community, business and personal services have doubled. The output shares of mining, manufacturing, construction, transportation, public administration and combined wholesale and retail trade have changed little.

Table 5.2: Industry Composition of Canadian GDP - 1926 and 2005 – per cent

	1926	2005
Agriculture, forestry, fishing and hunting	20.4	2.2
Mining and oil and gas extraction	3.2	3.8
Manufacturing	21.6	17.2
Construction industries	4.2	5.9
Transportation, warehousing, information and utilities	12.9	11.5
Wholesale trade	3.4	6.4
Retail trade	7.6	5.9
Finance and insurance, real estate	10.2	19.7
Community, business and personal service	12.2	22.0
Public administration	4.4	5.5

Based on nominal GDP at factor cost for 1926 and real GDP at factor cost for 2005.

The increased importance of finance, insurance, real estate and community, business and personal services has reduced the dependence of the total economy on physical inputs and therefore vulnerability to disruptions in the supply and transport of inputs. We assess arguments regarding changes in the importance of trade and in the production process in section 5.5.

5.2 The First World War

The First World War began in 1914 and the United States entered the War in 1917. The War ended in November 1918. Romer argues that European demand had already pushed the U.S. economy to full potential prior to America's formal entry in the war. Albala-Bertrand argues that low levels of idle capacity and unemployment can increase the probability that a natural shock will lead to production disruptions. In the war economy of 1918 there would have been few unused resources to bring to bear to offset illness-induced absenteeism, implying greater vulnerability to disruption than would hold today.

The War led to a significant increase in the female share of industrial employment, which in the United Kingdom rose from 26 per cent in 1914 to 36 per cent in 1918 (Broadberry and Howlett, 2003). Nevertheless, even in 1918 female participation would have been well below the levels of today. It follows that illnesses by children would today induce greater parental absenteeism to care for sick children than would have been the case in 1918. We incorporate this channel in our estimates of the impact of a future pandemic.

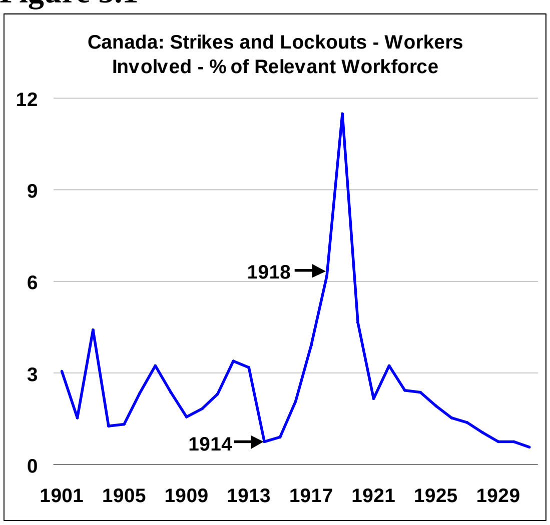
The IMF Avian Flu Working Group (2006) argues that a pandemic today would lead to greater absenteeism than in 1918 because "there may have been considerable social pressure on workers to stay at work" because the United States was at war. We do not know how much social pressure workers faced, but there is indirect evidence that can help us assess this claim.

Aggressive social distancing measures were widespread, suggesting that sick workers definitely did not face such pressures. In many places, people with any symptoms were forbidden to leave their dwelling. Some of the most aggressive social distancing measures—including quarantine—were tried in the armed forces itself (see Secretary of the Navy, 1919).

Did workplace-avoidance absenteeism fail to materialize because people were motivated by a sense of patriotic duty and fear of social opprobrium? Again, we cannot look into the minds of those alive in 1918. Workplace avoidance absenteeism is sometimes posited to stem from an overpowering, unreasoning fear that leads to intense efforts to avoid social contact. Cooper (2006) suggests that many people "would hunker down in their homes" and that "New Yorkers might head for the Hamptons [and] Torontonians for their cottages and farms." It would be surprising if so great a fear could have been completely negated by the mere fear of social disapproval in 1918. Regardless of the level absolute fear in 1918, the perceived relative risk of going to work may have been small. In this case, workplace avoidance absenteeism would have been small with or without the war.

Data on strike and lockout activity provides us with a means of evaluating the importance of war-related fear of social disapproval in 1918. Figure 5.1 shows the number of workers involved in strikes and lockouts in Canada as a percentage of the workforce employed outside the management, professional, sales and clerical occupations.

Figure 5.1



In the first year of the war, strike activity dropped sharply, consistent with notion that work stoppages were viewed as unpatriotic. As the war progressed, however, work stoppages soared, and in 1918 reached their second-highest level in the 1901-31 period. A similar pattern occurred in the United Kingdom where "the war brought about a distinct widening of the aims of labour" (Haimson and Tilly, 1989). These stoppages were likely concentrated in precisely those industries that were directly connected to the war effort. Social opprobrium would likely have been much greater for those who chose to withdraw their labour from such key industries in order to achieve higher wages than for those who simply failed to report for work during the height of the pandemic. In the confusion of the peak weeks of the pandemic work-avoidance absenteeism would likely not have been easily distinguishable from illness absenteeism.

This does not mean that those who struck for better pay or working conditions in 1918 were actually lacking in patriotism. They may simply not have equated being at work at all costs with the fulfillment of their patriotic duty. The fact that strikes surged to near-record levels in 1918 suggests that normal economic incentives were trumping fear of appearing insufficiently patriotic. It is hard to believe in such a context that fear of opprobrium was responsible for the absence of work-avoidance absenteeism in sectors like finance that were less directly related to the war effort than heavy industry.

The sharp decline in work stoppages apparent in Canada in 1914 did not occur in the United States in 1917 when it entered the war. U.S. work stoppages in 1917 were almost four times the level of 1914 and in 1918, three times the level of 1914. The lack of a “patriotic dip” in U.S. absenteeism is consistent with the fact that the U.S. entry into the war received was greeted with significant minority opposition. In the U.S. House of Representatives, fifty votes were cast against the U.S. declaration of war against Germany in April 1917, compared with virtual unanimity following the attack on Pearl Harbour in 1941. In Europe, the outbreak of the war in 1914 was greeted with great enthusiasm and the war was expected to be short. By 1917, such illusions had been dispelled.

5.3 Changes in the availability of leave

The IMF Working Group argues that “the lack of a formal safety net may have threatened workers with high financial costs in case of absenteeism from the workplace,” and thus helped to limit the economic impact of the 1918 pandemic. For this reason, as well war-related fear of social opprobrium, they argue that “it appears unlikely that a similar outbreak today would have comparably limited effects.”

For someone to engage in a workplace avoidance absence the perceived marginal benefit of reduced risk must exceed the marginal cost of the absence. This is central to the theoretical model of workplace avoidance absenteeism that we develop in Section 6.4 and Appendix B. The marginal cost of an absence depends upon the type of leave taken and its duration. Changes in leave provisions could in principle affect the incidence and duration of workplace avoidance absences.

In 1918, few non-management workers had paid leave of any kind. However, Allen (1969) estimates that 33 per cent of U.S. salaried workers received paid vacations during the First World War. Klein (2003) reports that by the end of World War I most white-collar workers had one or two weeks of paid vacation, but that “vacations, paid sick days, and disability insurance did not become general policy among manufacturing firms until after the Depression.”

In 2005, 58 per cent of all U.S. workers had access to paid sick leave, 77 per cent to paid vacations, 36 per cent to paid personal leave and 7 per cent to paid family leave. Those with paid personal leave had access to a median of two days (Hewitt Associates LLC, 2001).

It does not seem likely that the lack of sick leave in 1918 meant that many people worked who were ill with influenza. In many cities, public orders were enforced prohibiting people with symptoms from leaving their homes, and they certainly would not have been welcome at the workplace. The absence of sick leave undoubtedly meant that ordinary illness absenteeism was less in 1918 than today, however it was quickly recognized in 1918 that the Spanish Influenza was not an ordinary illness. Many more jobs were physically strenuous in 1918, and it would have been difficult for people to perform these while ill with influenza.

If workers in 1918 who had not yet fallen ill chose to remain at work because they considered the marginal risk reduction of workplace avoidance to be small, then the availability of leave provisions would had little effect on this choice. On the other hand, if they had considered the risk reduction to be large, then we should have seen evidence of significant workplace avoidance absenteeism even without widespread leave availability. For the lack of leave to have mattered, the perceived risk reduction would have had to have been just balanced off by the cost of the absence.

While many more workers have access to various types of leave today than in 1918, the cost of a work-avoidance absence may not be much less, particularly if it lasts more than a few days. Workplace avoidance is not a leave category in collective agreements. No employee benefit plans provide for paid leave for those who are afraid to come to work. Could other existing types of leave serve the same purpose? The closest substitutes would be personal and family leave, however accessibility to these types of leave is not widespread and the median number of days available is small. Workers could use vacation leave, however, this too is not unlimited and involves the cost of forgoing planned leisure at other times of the year. Most benefit plans only allow a few days of sick leave to be taken without a doctor's certificate, thus it would not be viable for an extended workplace avoidance. Most benefit plans also require pre-approval of vacation and personal leave, even if it is unpaid. It is unlikely that a firm would approve such leave if doing so jeopardized business continuity. Workers intent on avoiding the workplace could of course simply engage in an extended unpaid and unapproved absence, however, the same option (and associated costs) existed for workers in 1918.

We cannot rule out the possibility that the greater availability of leave today would imply more workplace avoidance absenteeism in a severe pandemic than appeared to occur in 1918. However, the characteristics of leave provisions would imply that such absences would tend to be considerably shorter than required to obtain the high work-avoidance estimates of some authors. Availability of telework would also reduce workplace avoidance absenteeism. Much also depends on how much risk reduction workers believe that they are receiving by avoiding the workplace, and whether this would have changed since 1918. We explore this issue in our discussion of changes in mass communications in Section 5.4.

The lack of sick leave in 1918 meant that those who fell ill would have suffered direct income losses with negative implications for consumer demand. This channel would be less pronounced today.

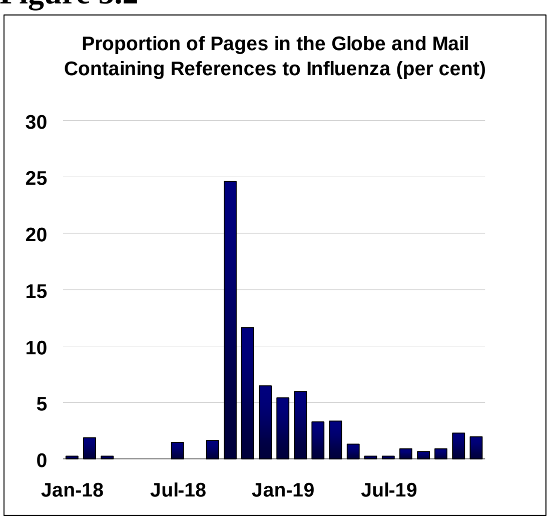
5.4 Changes in Mass Communications

Fan (2003) argues that the impact of SARS can be attributed to "the almost costless and rapid transmission of information due to the development of modern media and communication technologies." Given the prominence of psychologically-induced demand effects and workplace-avoidance absenteeism in the estimates of some analysts, it is worth investigating whether changes in the media and flow of information might cause these effects to be greater today.

The media has clearly changed in important ways since 1918. While entirely new forms of media now exist, advanced economies in 1918 had nevertheless already entered the world of mass global communication via transoceanic telegraph and telephone networks and large circulation newspapers.

The 1918 pandemic was extensively covered by newspapers of the period. Figure 5.2 shows the proportion of pages in the Toronto *Globe* that contained stories related to influenza in each month in 1918 and 1919. In the peak mortality month of October 1918, 25 per cent of all pages in the *Globe* contained such stories.

Figure 5.2



This coverage did differ in an important way from that which could be expected today. It usually received prominent coverage in the inside pages, however, news of the war dominated the front page. A severe pandemic today would clearly be the top news story. A mild pandemic, might, however receive limited coverage. The 1957 and 1968 pandemics both received much less newspaper coverage than the 1918 pandemic.

What was the nature of the 1918 newspaper coverage? Table 5.3 breaks down the coverage in the *Toronto Star* during the morbidity surge of September 23 to October 26.

Sixty-one per cent of the 84 articles published during this period focussed on mortality. This included reports on the number of deaths per day, on deaths of prominent persons and on the case mortality rate (of which an accurate estimate was quickly formed). The concentration of mortality among those aged 20 to 40 was also quickly noted. A number of reports stressed that daily death rates were at levels never before seen.

Forty-eight per cent of the articles reported that the situation was worsening, either in terms of an increase in the number of cases or of deaths.

Twenty-four per cent of the articles reported or urged the imposition of a number of social distancing measures, such as school closings, closings of churches and places of public amusement, bans on public gatherings (including conventions and auctions) and requirements that persons with symptoms remain in their homes. Reports noted the introduction of staggered work hours to reduce the density use of public transit during rush hours.

Table 5.3: Articles in the *Toronto Star* Dealing With the Influenza Pandemic: September 23 to October 26, 1918

Primary Focus of Article	Number	Per Cent
Mortality	51	60.7
Social Distancing Measures	20	23.8
Preventative Individual Health Measures	13	15.5
Symptoms/Treatment	8	9.5
Need to Remain Calm	4	4.8
Need for Government Action	5	6.0
Absenteeism	9	10.7
Stresses on Health Care System	10	11.9
Need for Health Care Volunteers	9	10.7
Actual or Predicted Situation Worsening	41	48.8
Actual or Case Rate Situation Under Control or Improving	10	11.9
Relationship to War	1	1.2
Other	5	6.0

Sixteen per cent of the articles described measures that individuals could take to avoid getting the flu, such as washing hands, wearing face masks and working and living in well-ventilated quarters.

Twelve per cent of the articles described stresses on the health care system arising from the combination of high case admissions and sickness among staff. Eleven per cent of articles (including public notices) called for volunteers to assist in caring for the sick.

Twelve per cent of articles reported that the situation was stable or improving, most of these late in the period when the death rate in Toronto was indeed peaking and had begun to fall in a number of Eastern U.S. cities.

Eleven per cent of stories reported impacts on absenteeism and on business. As described in Section 4, these convey a mixed picture in which much of the economy carried on as usual while particular sectors and work units were noticeably but briefly affected at the peak of the main wave. Advertisements suggest that retail business was carrying on. Some businesses stressed that they were thoroughly disinfecting their premises each night. Advertisements for facemasks and medicinal products were frequent and prominent.

The general picture one obtains from this coverage is that the situation was very serious. No one could have been unaware of this, particularly as people would have been living with the reality of the pandemic and with widespread social distancing measures.

Coverage today of a severe pandemic would not be overshadowed by an event like the First World War. Some media today could well give a pandemic almost continuous coverage, and some of this coverage could be more alarmist than that of 1918. It is unclear whether such coverage would lead to larger psychological demand and workplace avoidance impacts than in 1918. SARS received significant media coverage and this (along with WHO travel advisories) led to significant impacts on air travel to the affected locations. Survey data suggests that residents of Taiwan suffered from heightened anxiety during SARS, and media coverage doubtless played a role in this, yet they nevertheless continued to perform their daily routines (Liu *et al.*, 2003). Keller and Block (1996) find that messages that seek to arouse fear of a particular risk can have a smaller effect on behaviour than more subtle messages.

Any additional psychological demand effects would tend to be mitigated in the aggregate by expenditure reallocations. We explore the issue of possible workplace avoidance absenteeism in greater detail in Section 6.3.

5.5 Changes in the Production Process

A pandemic would create a disarticulation in the production process if it caused inventories of inputs to be exhausted via reduced production of inputs or reduced transportation of inputs to users. The economic data from 1918 suggest that no such disarticulations occurred. This is not surprising, as the pandemic impact on single-city illness absenteeism in 1918 likely peaked at around 5 ½ per cent, which would not have been sufficient to cause production disarticulations. For disarticulations to occur in a prospective pandemic, either significant workplace-avoidance absenteeism would need to occur in industries that produce or transport inputs, or the production process itself would need to be significantly more vulnerable to any supply chain disruptions that did occur.

Social and labour market changes since 1918 do not provide strong support for the notion that workplace-avoidance absenteeism would be much greater than in 1918. Such absenteeism would be particularly unlikely in emerging economies where personal leave would be less available and personal absences thus more costly than in advanced economies. High workplace absenteeism is also unlikely in goods transportation, as it is among the least socially dense sectors. In Section 5.4 and Annex B we develop a framework for estimating upper bounds to possible work-avoidance absenteeism.

Some analysts implicitly equate fear of personal travel with refusal by goods transporters to transport their goods. However, there is no evidence of any goods trade or transportation disruptions in either 1918 or 2003 during the SARS outbreak. Many people delayed personal travel to South Asia during SARS, but air cargo shipments were unaffected. Similarly, personal air and ground travel between Canada and the United States fell sharply in the immediate wake of the September 11 terrorist attacks but goods transportation was unaffected. The differing impacts on personal travel and goods transportation are not surprising given that the cost-benefit calculations are very different. The costs of delaying a personal trip to an affected location would likely have been perceived as very small compared with the supposed benefit of reduced risk. In contrast, for someone working in goods transportation the costs of not working are direct and significant. Many jobs contain an element of risk at the best of times, but people carry on even in adversity because they feel that it is their job to do so. This phenomenon is noted by Albala-Bertrand in his examination of natural disasters.

SARS developed in a few limited locations and did not spread easily. During the SARS outbreak the WHO issued travel advisories regarding affected cities and personal travel to these cities dropped sharply. While those engaged in goods transportation may have been worried about the presence of SARS in these locations, they nevertheless continued to perform their jobs and the flow of goods was unaffected. The WHO does not envisage issuing travel advisories during a pandemic as such measures would not be effective.

For supply chains to be disrupted enough to exhaust inventories, psychological impacts on those working in the transportation industry would need to be significantly greater than psychological impacts on demand. In effect, truckers would need to be more afraid to drive alone in their trucks than shoppers would be to go to the stores where the transported goods are sold. This is an improbable ordering of psychological impacts. It is even more improbable when one considers that influenza spreads much more easily than SARS and would likely affect most parts of North America simultaneously, albeit with differing peaks. Influenza would be much less localized than SARS, implying little difference in perceived risk in one location than another. In an expected sense, there would be no location-specific risk.

Disruptions to the supply and transportation of inputs thus seem unlikely. Nor is it obvious that the Canadian economy is more vulnerable to disruptions if they did occur than was the case in 1918.

The Canadian economy is not much more reliant on trade than in 1918 (Table 5.4). Total trade (exports plus imports) equalled 61 per cent of GDP in 1918, compared with 72 per cent in 2004. While some of the elevated trade in 1918 stemmed from the First World

War, it also reflected elevated trade flows associated with the first era of globalization, an era that gradually faded as protectionist measures in the 1920s were followed by the dislocations of the Great Depression. The importance of trade in the Canadian economy troughed in 1958, and the 1918 level of trade as a share of GDP was not reached again until the early 1990s.

Table 5.4: External Trade – Share of GDP

	1918	1929	1958	2004
Canada	60.9	49.8	34.6	72.2
USA	na	11.1	8.7	25.3

While the trend to "just-in-time inventories" has meant lower inventory-shipments ratios in manufacturing, this has not primarily taken the form of reduced inventories of inputs. This is particularly apparent in Canada's most trade-dependent industry – motor vehicles and parts. As Table 5.5 shows, most of the total decline in the inventory-shipments ratio in this industry has occurred in goods in process and finished goods. It reflects a more efficient management of the production process, rather than a shift to minimal holdings of inputs.

Table 5.5: Canadian Motor Vehicles and Parts Industry – Inventory-Shipments Ratio by Stage of Process

	1970	2005
Total	1.19	0.44
Raw Materials	0.32	0.24
Goods in Process	0.58	0.10
Finished Goods	0.28	0.10

In the United States, wholesale and retail inventory-shipments ratios were actually higher in 2005 than they were 60 years earlier (Table 5.6). This is consistent with Genest-Laplante's (2000) findings that big box stores have higher inventory-sales ratios than smaller retail stores. This is not surprising given that big-box stores are to some degree large inventory warehouses. By merging retail and wholesale functions, they can buy directly from suppliers and their management of orders is closely tuned to demand. However, again, a more effective management of inventories and orders has not meant reduced average inventory holdings – quite the opposite.

Table 5.6: U.S. – Inventory-Shipments Ratios

	1948	2005
Manufacturing	1.65	1.20
Wholesale	1.13	1.18
Retail	1.39	1.51

Finally, it is not obvious that the assembly line mode of production prevalent in 1918 was less vulnerable to disruption from absenteeism than the vertically integrated production of today that can flexibly avail itself of a variety of supply sources.

6 Estimating the Economic Impact of a Future Pandemic

In this section, we estimate impacts of a pandemic stemming from mortality and morbidity, from care-of -sick and possible workplace-avoidance absenteeism, and from psychologically induced demand changes.

6.1 Estimating Direct Mortality and Morbidity Impacts

We do not know how severe a future pandemic will be. We therefore benchmark our pandemic scenarios to historical episodes where we have information on morbidity and mortality. Our assumptions are summarized in Table 6.1, with further details provided in Annex D.

Table 6.1: Morbidity and Mortality Assumptions

	1918 Scenario	**1957 Scenario**
Clinical Attack Rate %	25	35
Average Duration of Illness (days)	7	5
Population Mortality Rate (%)	0.43	0.04

In a 1918 scenario, we assume a multiple-wave cumulative clinical attack rate of 25 per cent. We assume that symptoms last 7 days on average and that cumulative population mortality reaches 0.43 per cent, implying a case mortality rate of 1.8 per cent. While Kilbourne (2003) estimates that symptoms lasted 3-5 days for most patients, we assume a higher average duration to capture the longer illnesses experienced by those suffering pneumonia as a complication. We assume that the age distribution of case mortality follows the "W" shape observed in 1918, and that the morbidity rate declines with age as in 1918.

In a 1957 scenario, we assume a multiple-wave cumulative clinical attack rate of 35 per cent. We assume that symptoms last 5 days[1] on average and that population mortality reaches 0.04 per cent, implying a case mortality rate of 0.1 per cent. We assume that the age distribution of case mortality follows the standard "U" shape observed in 1957 and

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[1] The gross attack rate during the 1957-58 pandemic is widely regarded to have been about 35 per cent. Since we know monthly excess illness absenteeism for Canada in 1957-58, we can then calculate the implicit average case duration as follows:

Average duration = (Cumulative monthly excess absenteeism rate)*365/(100*12*.35)

Canadian excess illness absenteeism rates were as follows during the 2 main waves of the 1957-58 pandemic:

Sep-57 0.73; Oct-57 3.05; Nov-57 1.06; Dec-57 0.43; Jan-58 0.39; Feb-58 0.19; ***Total 5.85***

Applying the cumulative monthly excess absentee rate to the above formula yields an implicit average case duration of 5.08 days.

that the morbidity age distribution follows that observed in Kansas City in 1957, with peak morbidity in the 15-20 age group (see Monto (1987)).

We estimate mortality effects on GDP by applying the respective age-specific mortality impacts to the current structure of the Canadian labour force. This yields an aggregate hours worked impact of –0.38 per cent in the 1918 scenario and a near zero impact in the 1957 scenario. GDP mortality impacts are obtained from an aggregate Cobb-Douglas production with an output-hours elasticity of 0.6. The resulting mortality impact on GDP is –0.23 per cent in the 1918 scenario.

We estimate morbidity effects on GDP by applying the respective age-specific morbidity impacts to the current structure of the Canadian labour force. This yields an aggregate hours worked impact of –0.47 per cent in both the 1918 and 1957 scenarios. GDP morbidity impacts are obtained using two alternative assumptions regarding the impact of absenteeism on output. In a high impact case, we use the aggregate Cobb-Douglas production function with an output-hours elasticity of 0.6. The resulting morbidity impact on GDP is –0.28 per cent in both scenarios. There is, however, microeconometric evidence that absenteeism shocks have much smaller effects on output than would be implied by the Cobb-Douglas production function. As Allen (1983) notes "at first glance the cost of absenteeism would seem to consist of merely the goods and services that would have been produced if the worker had reported … however … firms can partially offset the output loss through such adjustments as working employees overtime, reassigning workers from other positions, or hiring temporary replacements." Chartered banks in Toronto reported increased use of overtime to cope with head office absenteeism in October 1918 (*Toronto Star,* October 12 1918).

Using pooled U.S. data, Allen estimates that a 1 percentage-point increase in the absenteeism rate reduces output by 0.16 per cent. The Cobb-Douglas elasticity of 0.6 measures the permanent impact on output of a permanent change in hours worked and is therefore appropriate for measuring mortality impacts. Absenteeism impacts could be expected to smaller given that they are known to be temporary. In a low impact case, we thus use an output-hours elasticity of 0.2. The resulting morbidity impact on GDP is –0.09 per cent in both scenarios.

6.2 Estimating Care of Sick Absenteeism

A number of studies assume that a pandemic will cause people to miss work in order to care for sick family members. We estimate the impact of illness absenteeism on personal and family absenteeism using data from the Canadian Labour Force survey. Figure 6.1 shows illness and personal/family absenteeism since 1987. The seasonal variation in illness absenteeism is very noticeable, with spikes generally occurring in the normal flu season at the beginning of each year. We transform this data into first-differences in order to render it stationary. Figure 6.2 shows the resulting series since 1996 in order to make the correlation more visually apparent.

Figure 6.1

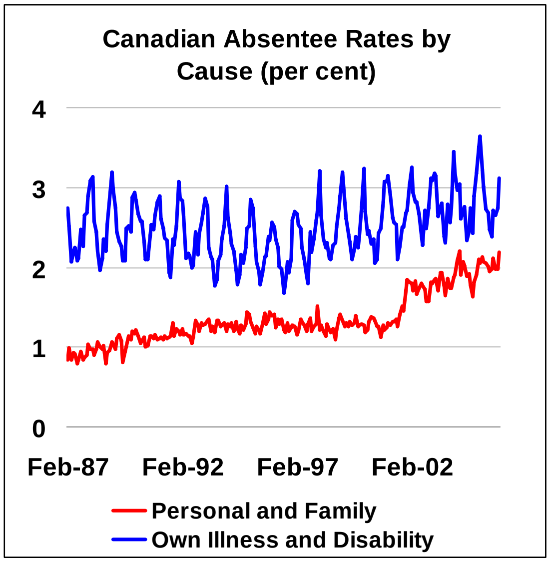
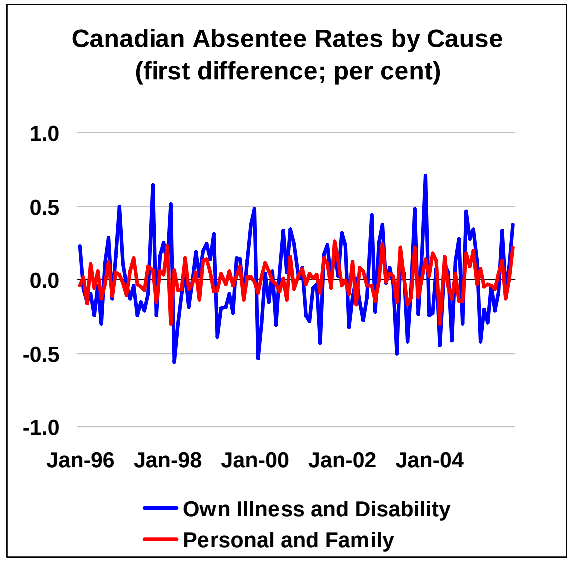


Figure 6.2



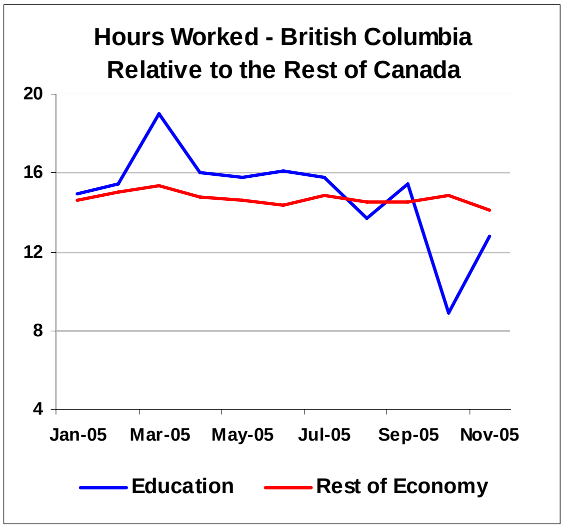
To capture the impact of shocks to illness absenteeism we regress the monthly first difference of the personal/family absenteeism rate on the monthly first difference of the illness absenteeism rate. The estimated elasticity is 0.12 with a standard error of 0.02. Applying this elasticity to our estimated morbidity impacts yields care-of-sick impacts on hours worked of –0.05 per cent in the 1918 scenario and –0.06 per cent in the 1957 scenario. These translate into GDP impacts of –0.03 per cent given a high output elasticity of 0.6 and –0.01 per cent given a low elasticity of 0.2.

6.3 Estimating Absenteeism Related to Possible School Closings

Schools closings were widespread during the main wave of the 1918 pandemic and are often mentioned as a possible social distancing measure in a future pandemic. Much higher female labour force participation today than in 1918 means that school closings taoday might cause greater absenteeism from work than would have been the case in 1918.

The British Columbia teachers' strike in October 2005 provides a useful test case to gauge the degree to which school closings would cause workers to take time off to care for their children. All British Columbia public schools and kindergartens were closed for a 2-week period in October 2005. This period included the Labour Force Survey reference week. Figure 6.3 shows raw hours worked in British Columbia relative to the rest of Canada in the education services industry and in all industries excluding education. We divide by hours worked in the rest of Canada in order to control for Canada-wide factors affecting hours worked. Not surprisingly, the impact of the school closings on hours worked in the education industry was very significant, however, hours worked actually rose in other industries. It is possible that the school closings did force some parents to stay at home to care for their children, however, such effects are too small to appear in the aggregate data.

Figure 6.3



The effects of the school closings were likely small for two reasons. First, some parents likely had access to informal care arrangements such as non-working relatives or friends or neighbours. Others may have brought their children to the workplace. While the latter might seem less likely during a pandemic, our analysis of workplace avoidance absenteeism in Section 6.3 suggests that the dynamics of infection and recovery would rapidly reduce the perceived relative risk of the workplace as the main wave developed in a particular location. Second, only a small proportion of the workforce would actually need to make alternative arrangements in the event of school closings. Table 6.2 shows the proportion of economic families in which all adults are working and the family includes kindergarten and elementary-school aged children but not teenagers. We exclude families with teenagers as parents would be unlikely to take time off to care for them, and teenagers might themselves be employed as caregivers for younger siblings. Only 3.6 per cent of the workforce would need to make alternative arrangements in the event of school closings. The British Columbia experience suggests that many of these had access to alternative arrangements that did not require them to miss work.

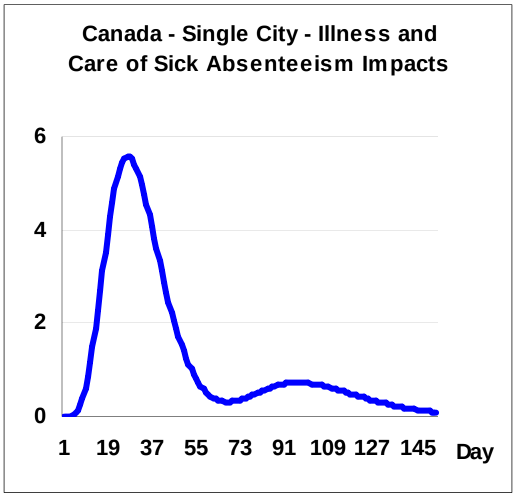
Table 6.2: 2001 Canadian Census – Economic Families with Kindergarten and Elementary School Age Children and No Children Age 12 and Over

	Number	Per cent
Total Economic Families	8273221	100.0
Adult members all working full year; at least 1 child 6-10, no children under 1 or 13-14	435625	2.9
Adult members all working full year; at least 1 child 4-5, no children under 1 or 13-14	205070	1.4
Minus economic families in both categories	98815	0.7
Total Economic Families Vulnerable	541880	3.6

In our base case forecast we do not assume any absenteeism stemming from school closings, however, the prudent planning assumption for peak absenteeism reported in Section 6.4 allows for the possibility that part of the affected workforce might need to be absent from work.

Figure 6.4 shows the daily pandemic impact on illness and care of sick absenteeism rates in a single city for a 1957-type pandemic. This, it will be recalled, assumes a 35 per cent gross attack rate over two waves, with an average illness duration of 5 days. Illness absenteeism would be very similar in a 1918 scenario featuring a 25 per cent attack rate over two waves with an average illness duration of 7 days.

Figure 6.4



We next estimate peak all-cause absenteeism by industry for a single city. Industry heterogeneity will reflect heterogeneity in normal February all-cause absenteeism and heterogeneity in peak morbidity. To capture the latter, we first regress monthly changes in each industry's illness absenteeism rate on changes in the all-industry rate. Coefficients are provided in Table 6.3. A typical 1 point change in the all-industry absenteeism rate is associated with a greater than 1 point change in transportation and warehousing, education, health care and social assistance, and public administration.

We hypothesize that much of the variability in Table 6.3 reflects differences in sick leave availability and in social density across industries. For typical illnesses, greater leave availability would tend to imply greater illness absenteeism. In a severe influenza pandemic, however, this source of heterogeneity would likely disappear given that sick workers would be strongly advised (or even required) to remain home. Heterogeneity stemming from differences in social density would remain. More socially dense industries could be expected to experience a more compressed morbidity distribution with a higher daily illness absenteeism peak.

Table 6.3: Response of Monthly Changes in Industry-Specific Illness Absenteeism Rates to Changes in the All-Industry Illness Absenteeism Rate

	Coefficient	Standard Error
Goods	0.912	0.044
Agriculture	na	na
Forestry, Fishing, Mining, Oil and Gas	0.590	0.139
Utilities	0.516	0.422
Manufacturing	0.894	0.058
Services	1.038	0.018
Trade	0.908	0.059
Transportation & Warehousing	1.103	0.136
Finance, Insurance and Real Estate	0.911	0.092
Professional, Scientific and Technical Services	0.687	0.110
Educational Services	1.488	0.105
Health Care and Social Assistance	1.312	0.092
Information, Culture and Recreation	0.403	0.104
Accommodation and Food Services	0.697	0.102
Other Services	0.683	0.119
Public Administration	1.472	0.104

Table 6.4: Industry Social Density and Unionization Rates

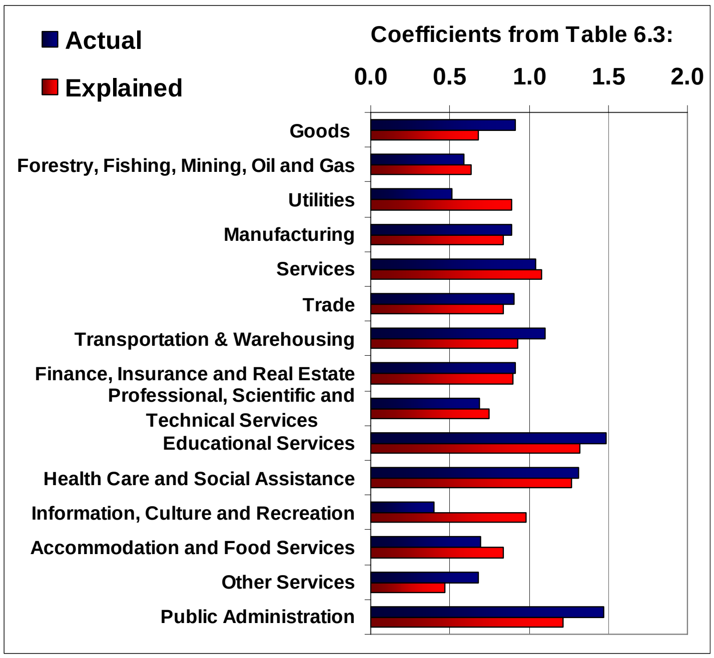
	% Low Social Density	% Unionized
All Industries	27.1	39.6
Goods	63.0	44.0
Agriculture	96.9	7.7
Forestry, Fishing, Mining, Oil and Gas	69.3	55.7
Utilities	55.7	73.9
Manufacturing	51.3	48.0
Services	15.2	38.6
Trade	12.6	12.9
Transportation and Warehousing	42.3	48.3
Finance, Insurance and Real Estate	3.3	13.1
Professional, Scientific and Technical Services	11.7	8.3
Educational Services	2.4	79.3
Health Care and Social Assistance	3.8	64.9
Information, Culture and Recreation	24.2	32.4
Accommodation and Food Services	5.4	10.6
Other Services	43.1	6.7
Public Administration	12.8	65.1

Table 6.4 reports social density and unionization rates by industry. We calculate social density rates by cross tabulating individual occupation data into individual industries. Agriculture is the least socially-dense industry while education services is the most socially-dense. Finance, insurance and real estate is the second most socially dense industry. Transportation and warehousing is significantly less socially dense than the all-

industry average. The unionization rate proxy suggests that supplementary leave benefits are more widely available in education services, utilities, public administration and health care and social assistance.

To test our hypothesis, we regress the coefficients from Table 6.3 on the corresponding industry social density and unionization rate variables. Regression results are reported in Table D.6 of Annex D. Both explanatory variables are statistically significant and we are able to explain about half the variation in the industry coefficients. This suggests that these variables have high information content with respect to absenteeism behaviour. Actual and explained coefficient values are shown in Figure 6.5.

Figure 6.5: Coefficients from Table 6.3: Actual and Explained by Industry Social Density and Unionization Rates



To capture heterogeneity that stems from social density alone (and that is likely related heterogeneous morbidity peaks) we adjust the explained values in Figure 6.5 by setting the unionization variable (which proxies leave availability) at its all-industry average. The resulting adjusted coefficients are shown in Table 6.5.

Table 6.5: Adjusted Response of Monthly Changes in Industry-Specific Illness Absenteeism Rates to Changes in the All-Industry Illness Absenteeism Rate (Morbidity Peak Social Density Effects)

	Coefficient
Goods	0.655
Agriculture	na
Forestry, Fishing, Mining, Oil and Gas	0.558
Utilities	0.750
Manufacturing	0.798
Services	1.087
Trade	1.103
Transportation & Warehousing	0.887
Finance, Insurance and Real Estate	1.156
Professional, Scientific and Technical Services	1.108
Educational Services	1.160
Health Care and Social Assistance	1.153
Information, Culture and Recreation	1.029
Accommodation and Food Services	1.144
Other Services	0.879
Public Administration	1.102

These coefficients are multiplied by the peak all-industry illness absenteeism impact to obtain the industry-specific illness absenteeism impacts (see Table 6.6). Low social density industries like goods and transportation and warehousing feature lower morbidity peaks, while many services industries, and, in particular, education and health care and social assistance, feature higher peaks.

Table 6.6: Estimated Daily Peak Absenteeism by Industry in a Single City

	Normal February All-Cause Absenteeism	Illness and Care of Sick Absenteeism	Peak February All-Cause Absenteeism
All Industries	8.0	5.6	13.6
Goods	8.1	3.9	11.9
Agriculture	7.0	3.1	10.0
Forestry, Fishing, Mining, Oil and Gas	9.9	3.4	13.3
Utilities	8.5	4.3	12.8
Manufacturing	7.5	4.6	12.0
Services	8.0	6.0	14.0
Trade	7.0	6.1	13.0
Transportation & Warehousing	9.5	5.0	14.5
Finance, Insurance and Real Estate	7.2	6.3	13.5
Professional, Scientific and Technical Services	6.3	6.1	12.4
Educational Services	7.5	6.4	13.9
Health Care and Social Assistance	11.1	6.3	17.5
Information, Culture and Recreation	3.8	5.7	9.6
Accommodation and Food Services	6.4	6.3	12.7
Other Services	6.5	5.0	11.5
Public Administration	9.4	6.1	15.4

Table 6.6 also provides our base case estimates of peak all-cause absenteeism in a single city by industry. This equals normal February all-cause absenteeism in that industry plus the peak impact on illness and care of sick absenteeism. Peak all-cause absenteeism ranges from 17.5 per cent in health care and social services to 9.5 per cent in information, culture and recreation services. All-industry all-cause absenteeism peaks at 13.6 per cent.

6.4 Evaluating Possible Workplace-Avoidance Absenteeism and Establishing Prudent Peak Absenteeism Planning Assumptions

Some argue that a severe pandemic could lead to significant workplace-avoidance absenteeism, as workers would stay home out of fear of contracting the flu at work. The IMF World Economic Outlook describes this as resulting from "widespread panic" and suggests that total absenteeism could average 30 per cent over a period of 6 weeks, reflecting illness, workplace avoidance and care of the sick. Kennedy, Thomson and Vujanovic (2006) assume total absenteeism of 20 per cent over a full quarter "as workers seek to avoid infection by staying away from their workplaces." Cooper (2005) suggests that "many would hunker down in their homes." The IMF Avian Flu Working Group says "absenteeism could become so widespread that staffing for the most critical operations may become inadequate, and succession plans may no longer provide for continuity."

As the previous section demonstrated, pandemics like those of 1918 and 1957 would boost illness and care of the sick absenteeism by between 5 and 5 ½ percent on the peak day in a single city. With normal total absenteeism in February of 8 per cent, this implies total peak day absenteeism of around 13 per cent and average absenteeism of 10.5 per cent during the six weeks centred around the peak day. To achieve average total absenteeism of 30 per cent over six weeks would thus require average workplace-avoidance absenteeism of 20 per cent over the same period, or five times the amount of absenteeism induced by illness from influenza.

Jonung and Röger correctly note the speculative nature of such workplace-avoidance absenteeism assumptions. While arbitrary scalings of illness absenteeism can certainly generate large impacts, they are not grounded in theory or experience. As we have seen, there is no evidence of significant workplace-avoidance absenteeism during any previous pandemic, or during SARS.

While leave benefits are more generous than in 1918, it is not clear that the marginal cost of an extended workplace-avoidance absence is much below that of 1918. The lack of apparent widespread workplace-avoidance absenteeism in 1918 may have stemmed from the coping strategies described by Slemrod (2003); strategies that were likely again at work in locations affected by SARS. Empirical support for the importance of such strategies is provided by Weinstein (2005) who cites a survey of New Jersey adults in which three-quarters of respondents said that they faced a below-average risk of contracting influenza. For these reasons, we do not assume any workplace-avoidance absenteeism in our base case pandemic impact estimates. Nevertheless, it is prudent, particularly for those engaged in business continuity planning, to consider the possibility that some workplace-avoidance absenteeism might occur.

Our objective is to estimate an upper bound for the path of workplace-avoidance absenteeism in a single location over the main wave of a pandemic. To accomplish this we develop a model of work-avoidance absenteeism that is described in detail in Appendix C. Its essential outlines are as follows.

In the event of a pandemic, some workers in socially-dense occupations may believe that their ultimate probability of contracting the disease would be lowered by being absent from the workplace at some point in time. We assume that the cost of an absence increases with its duration, and that the marginal cost also increases, reflecting the fact that the employee would need to use increasingly costly leave options as the absence continues. Not all workers who attach a positive relative risk to their workplace will plan on a workplace-avoidance absence. The perceived benefit must exceed the cost for an absence to be planned. We denote those workers who plan to take a workplace-avoidance absence as the *vulnerable workforce.*

The vulnerable workforce will not be fixed in time. Workers will cease to plan on a workplace-avoidance absence if they become clinically ill and recover, or if someone in their household contracts influenza. Those who recover will have acquired immunity and would have no reason to fear again contracting the disease. Those living with a sick person would not likely regard the workplace as less risky than being at home, and would have a diminished view of the efficacy of any risk-avoidance measure.

We assume that the perceived risk of contracting the disease in the workplace relative to alternative venues is proportional to the local morbidity rate. At each point in time, workers update their expectations about the future morbidity path. Expected paths can vary across workers and need not be accurate *ex ante*.

Workers begin a workplace-avoidance absence if the marginal benefit of the perceived risk reduction exceeds the marginal cost of the absence in terms of foregone pay or future leave. They terminate the absence when the perceived marginal benefit falls below the marginal cost. The starting and ending points of the spell are determined jointly given that the marginal cost is a function of the duration of the absence. The duration of a planned absence will be decreasing in the cost of leave and increasing in the perceived relative risk of the workplace. The expected mid-point of the workplace-avoidance absence path will be close to the expected workplace morbidity peak given a fairly symmetric expected morbidity path. Those that begin a workplace-avoidance absence earlier in the pandemic are thus likely to plan on a longer absence than those that begin later.

If a worker revises her expectations of the future morbidity path after beginning an absence spell, then the spell will terminate at a time different from that initially planned. If a worker overestimates the length of the morbidity wave, then she will start her absence spell later than if the true path had been originally expected. The spell will also end earlier than had been planned at the time the spell began.

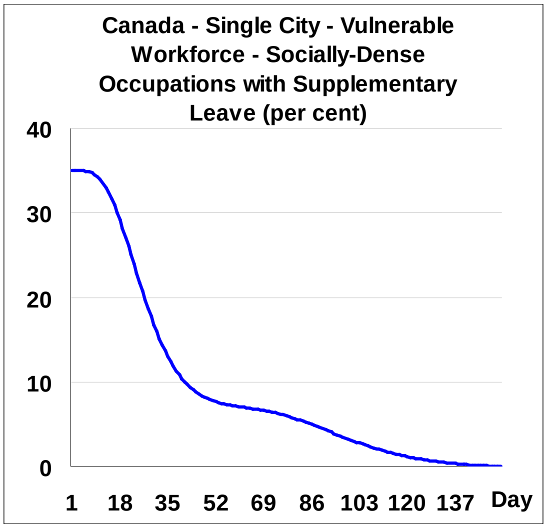
We model the incidence of new workplace-avoidance spells by combining the qualitative predictions of our model with historical experience and the characteristics of modern leave provisions. The high cost of extended absences suggests that few spells would begin early in the wave. Anyone beginning an absence early would plan on it lasting a long time – up to 50 days. We consider two new workplace-avoidance incidence assumptions. First, we assume that new workplace avoidance incidence is proportional to and coincident with the new illness incidence, and second, that it lags the new illness incidence path. Both assumptions are consistent with a wide distribution of perceived relative workplace risk and of cost of leave across the vulnerable group. A proportional coincident path is consistent with workers correctly anticipating the shape of the local morbidity path. Workplace-avoidance incidence would lag new illness incidence if awareness of local morbidity lags actual morbidity, or if the duration of the wave is overestimated, or if perceived relative risk is partly a function of actual local case mortality.

We assume that 35 per cent of those working in socially dense occupations that feature supplementary leave benefits (e.g., sick leave and some form of personal family leave) will plan at the beginning of the local main wave on taking a workplace-avoidance absence at some point in time. We proxy the proportion of the workforce with access to supplementary leave benefits by the unionization rate. We assume that 17.5 per cent of those working in socially dense occupations that do not feature supplementary leave benefits will plan on taking a workplace-avoidance absence at some point in time.

Our choice of 35 per cent reflects a number of factors. First, this proportion appears to have been zero in 1918. Second, not all workers in socially dense occupations would perceive the workplace as riskier. Third, not all workers who do perceive the workplace as riskier would actually plan on a workplace-avoidance absence. The marginal cost of such an absence could be significant even for workers with supplementary leave benefits. Fourth, a survey of Maryland public health workers conducted by Balicer *et al.* (2006) found that 54 per cent of workers indicated a willingness to report to work during an influenza pandemic. Clinical staff were significantly more likely to express a willingness to report to work than support staff. A negative response to such a survey is costless, unlike an actual workplace-avoidance absence. This suggests that the actual proportion of workers who would plan to work throughout the pandemic could be higher. Non-clinical public health workers might also have a higher perception of workplace risk than workers in most other industries. Together, these factors suggest that our assumption is prudent.

Figure 6.6 shows the evolution of the vulnerable workforce in socially dense occupations with supplementary leave benefits. Initially, 35 per cent plan on an absence, however this proportion declines as more and more households experience cases of influenza and the perceived relative risk of the workplace declines. The vulnerable workforce declines most sharply at the peak of case incidence.

Figure 6.6



Consistent with the results of our loss-minimization model, we assume that the expected duration of an absence spell is greater the earlier the absence begins. If everyone knew the exact future morbidity path in advance, then no spells would begin after the morbidity peak. In reality, the future path will not be known with certainty and workplace-specific peaks will vary and will be distributed around the local peak. We assume that those who begin an absence at the beginning of the local main wave plan, on average, to be absent for 25 days. The average expected duration decreases in a linear fashion as the wave progresses, reaching 3 days for workers who plan to begin an absence at what they perceive to be the local morbidity peak. Our results are robust to more pessimistic choices of average duration as longer planned absences are often truncated by exits from the vulnerable population (see Annex C).

Figure 6.7 shows resulting workplace-avoidance absenteeism in a single city in socially-dense occupations with supplementary leave benefits. If new workplace-avoidance incidence is coincident with new illness incidence, then workplace avoidance absenteeism peaks at 6.3 per cent (half of this is in socially dense occupations without supplementary benefits) and all-cause absenteeism at 20 per cent (Figure 6.8). This scenario is consistent with workers correctly anticipating the path of morbidity. If new workplace avoidance incidence lags illness incidence by 2 weeks, then daily absenteeism peaks at less than 2 per cent and all-cause absenteeism at 15 per cent. This scenario is consistent with workers overestimating the duration of the pandemic. Workplace-avoidance absenteeism is lower in this case because the vulnerable population falls in line with cumulative illness incidence. This illustrates that more pessimistic expectations of the pandemic's severity can actually imply smaller rather than larger indirect effects.

Figures 6.7 and 6.8: Canada – Single City Absenteeism – Socially Dense Occupations with Supplementary Leave

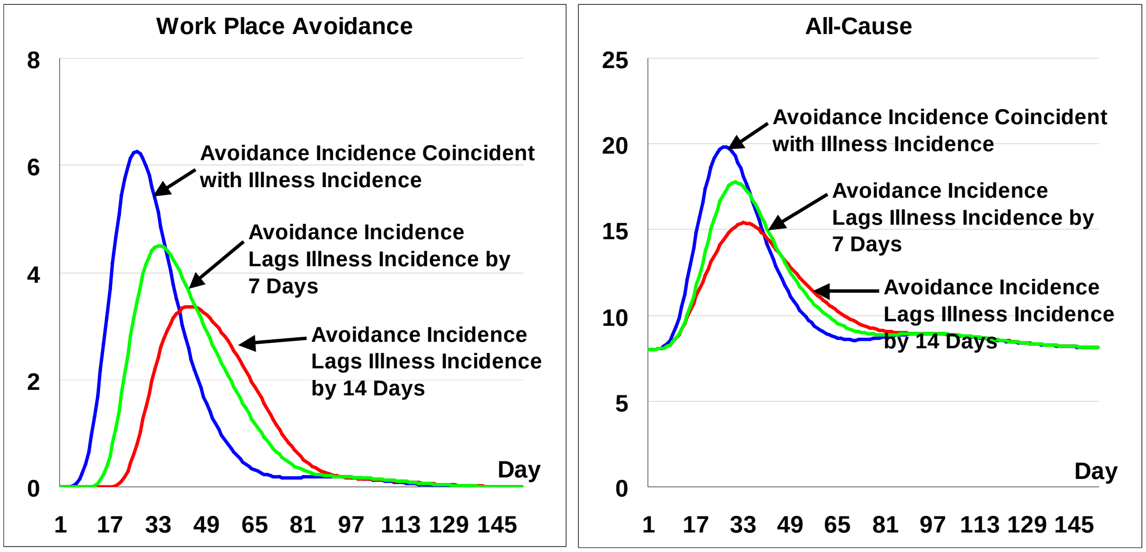


Table 6.7 provides our estimates of peak workplace-avoidance absenteeism in individual industries. It is highest in education services, health care and social assistance and public administration, reflecting a combination of high social density and unionization rates. While finance, insurance and real estate is one of the most socially-dense industries, its unionization rate is low, thus its workplace-avoidance absenteeism is close to the all-industry average. Workplace-avoidance absenteeism is below the all-industry average in transportation and warehousing.

Even when individuals correctly estimate the morbidity path, health care and social services is the only industry in which daily all-cause absenteeism peaks above 20 per cent (Table 6.8). The daily peak is 17.7 per cent in transportation and warehousing and 16.2 per cent in finance, insurance and real estate. In a low social density occupation like truck driving, peak absenteeism of around 15 per cent could be expected, belo the all-industry average of 16.8 per cent. All-industry absenteeism averages 13 per cent in the six weeks centred at the peak (Figure 6.9a). Absenteeism rates of these magnitudes are no higher than summer holiday peaks (Figure 6.9b), although a given peak pandemic absenteeism would likely be more disruptive than equivalent holiday absenteeism. Managers typically approve holiday leave in advance so as to stagger leave and ensure that a minimum contingent of key personnel remain on the job to cover for those who are absent. In a pandemic, managers would not be able determine in advance who would be absent, although they would retain some buffer in their ability to withhold approval of other types of leave. On balance, absenteeism peaks of these magnitudes should not be sufficient to cause widespread significant disruptions to goods transportation, utilities and payments systems.

If we assume that 70 per cent of those working in socially dense occupations would plan a workplace-avoidance absence then all-industry absenteeism peaks at 20 per cent and averages 15 per cent in the six weeks centred at the peak – still not likely enough to cause the disruptions that some studies predict. Without such disruptions, the scope for indirect effects shrinks.

Table 6.7: Estimated Daily Peak Work Place Avoidance Absenteeism by Industry in a Single City; Avoidance Incidence Coincident and Lagging Illness Incidence

	Coincident	Lags 7 Days	Lags 14 Days
All Industries	3.2	2.3	1.7
Goods	1.7	1.2	0.9
Agriculture	0.1	0.1	0.1
Forestry, Fishing, Mining, Oil and Gas	1.5	1.1	0.8
Utilities	2.4	1.7	1.3
Manufacturing	2.3	1.6	1.2
Services	3.7	2.6	2.0
Trade	3.1	2.2	1.7
Transportation & Warehousing	2.7	1.9	1.4
Finance, Insurance and Real Estate	3.4	2.5	1.8
Professional, Scientific and Technical Services	3.0	2.2	1.6
Educational Services	5.5	3.9	2.9
Health Care and Social Assistance	5.0	3.6	2.7
Information, Culture and Recreation	3.1	2.3	1.7
Accommodation and Food Services	3.3	2.4	1.8
Other Services	1.9	1.4	1.0
Public Administration	4.5	3.2	2.4

Table 6.8: Estimated Daily Peak All-Cause Absenteeism by Industry in a Single City; Avoidance Incidence Coincident and Lagging Illness Incidence

	Coincident	Lags 7 Days	Lags 14 Days
All Industries	16.8	15.7	14.3
Goods	15.3	14.7	14.0
Agriculture	12.6	12.6	12.5
Forestry, Fishing, Mining, Oil and Gas	17.0	16.4	15.8
Utilities	16.5	15.6	14.6
Manufacturing	15.3	14.5	13.5
Services	17.2	16.0	14.5
Trade	15.6	14.5	13.2
Transportation & Warehousing	17.7	16.8	15.7
Finance, Insurance and Real Estate	16.2	15.0	13.6
Professional, Scientific and Technical Services	14.8	13.8	12.5
Educational Services	18.5	16.7	14.6
Health Care and Social Assistance	21.6	20.0	18.0
Information, Culture and Recreation	12.5	11.4	10.1
Accommodation and Food Services	15.3	14.1	12.8
Other Services	14.0	13.3	12.5
Public Administration	19.4	17.9	16.1

Individual work unit peaks would vary across a given location while extended school closings could require part of the 3.6% of the affected workforce to be absent from work.

Adding prudence that includes these factors and estimated peak workplace-avoidance absenteeism (coincident case) yields planning assumptions in the 20-25 per cent range (see Table 6.9).

Table 6.9: Daily Peak All-Cause Absenteeism by Industry in a Single City – Prudent Planning Assumption (per cent)

	Normal	Illness and Care of Sick	Prudence	Total
All Industries	8.0	5.6	6.4	20.0
Goods	8.1	3.9	4.9	16.9
Agriculture	7.0	3.1	3.3	13.4
Forestry, Fishing, Mining, Oil and Gas	9.9	3.4	4.7	18.0
Utilities	8.5	4.3	5.6	18.4
Manufacturing	7.5	4.6	5.5	17.6
Services	8.0	6.0	6.9	20.9
Trade	7.0	6.1	6.3	19.4
Transportation & Warehousing	9.5	5.0	5.9	20.4
Finance, Insurance and Real Estate	7.2	6.3	6.6	20.1
Professional, Scientific and Technical Services	6.3	6.1	6.2	18.6
Educational Services	7.5	6.4	8.7	22.6
Health Care and Social Assistance	11.1	6.3	8.2	25.6
Information, Culture and Recreation	3.8	5.7	6.3	15.8
Accommodation and Food Services	6.4	6.3	6.5	19.2
Other Services	6.5	5.0	5.1	16.6
Public Administration	9.4	6.1	7.7	23.2

Figure 6.9a

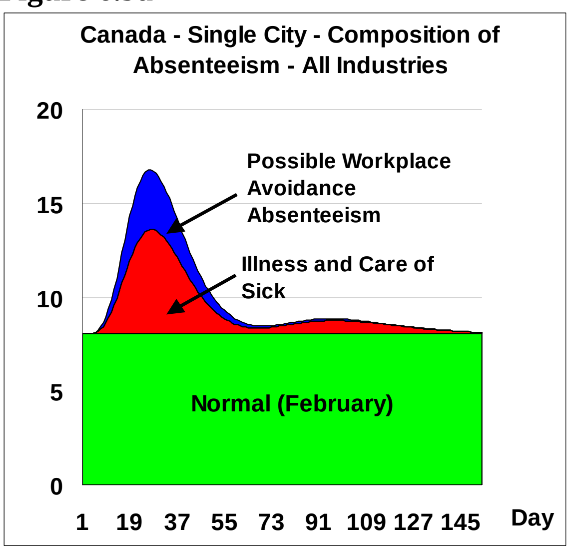
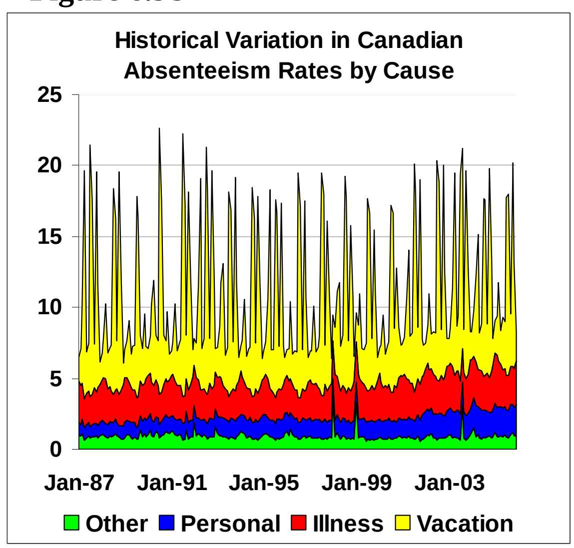


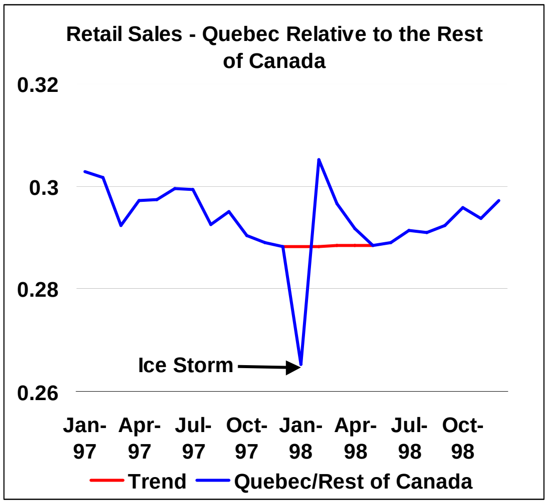
Figure 6.9b



6.5 Estimating Indirect Demand Impacts

While indirect demand impacts could be important for some sectors, aggregate macroeconomic impacts will be limited by reallocations of spending from sensitive service sectors to other sectors, the continuity of underlying income, the short duration of the event and the temporal reallocation of spending to the post-event period. Temporal reallocation was very noticeable in U.S. consumption following the September 11 2001 terrorist attacks and in Quebec retail sales following the 1998 ice storm that shut down much of that province's electricity grid for several weeks (see Figure 6.10).

Figure 6.10



Sector-specific demand effects cannot be estimated with precision. Passenger air transportation and accommodation were affected during SARS, as well as restaurant receipts in Hong Kong (down about 10 per cent for 1 quarter). Retail sales appear to have been unaffected during past pandemics and during SARS.

In our base case we assume that a 1918-type pandemic would lead to quarterly output level declines of 3 percent in retail and wholesale, 35 per cent in arts, recreation, accommodation and food service and 50 per cent in air transportation. This yields an annual GDP impact of –0.4 per cent in the absence of intersectoral and intertemporal reallocations. The assumed arts, accommodation and food services impact is 16 times that observed in Canada during SARS and the assumed air transportation impact is 14 times that observed during SARS. The total impact is 11 times that observed during SARS.

While it is certainly possible that impacts on individual industries could be larger, the implication for aggregate GDP would not be great once one accounts for probable expenditure reallocations. Such reallocations would be particularly likely in the retail sector. Purchases of necessities would continue, planned purchases might be delayed, and some discretionary purchases would be reallocated across industries. Boosting the arts, entertainment and recreation and entertainment impact to –100 per cent for a full quarter would only add 0.1 percentage points to our GDP impact estimate.

Although no effects are apparent during the actual 1957 pandemic, we assume that a future 1957-type pandemic would lead to indirect demand impacts double those observed during SARS.

6.6 Aggregate Total GDP Impacts

Tables 6.10 and 6.11 summarize our estimates of the impacts that 1918 and 1957-type pandemics would have on Canadian GDP (results for the United States are very similar). If absenteeism has a "high" impact on output (i.e., the long-run production function elasticity of 0.6 holds) and if there are no intertemporal or intersectoral demand reallocations, then a 1918-type pandemic would reduce GDP growth by 0.92 per cent in the pandemic year. Growth would be 0.64 percentage points higher than otherwise in the subsequent year, reflecting the recovery of output from absenteeism and indirect demand effects. If workplace avoidance were to occur as estimated in Section 6.3, then the total GDP impact would rise to 1.08 per cent. If all indirect effects are reallocated, the GDP impact would be –0.55 per cent without workplace avoidance absenteeism and –0.7 per cent with such absenteeism.

If absenteeism has a "low" impact on output (as suggested by microeconometric evidence) and if there are no intertemporal or intersectoral reallocations, then a 1918-type pandemic would reduce GDP growth by 0.72 per cent in the pandemic year. Full reallocation reduces the impact to –0.35 per cent.

Table 6.10: 1918 Pandemic Scenario – Impacts on Pandemic Year GDP

	High Absenteeism Impact on Output		Low Absenteeism Impact on Output	
	No Demand Reallocation	Full Demand Reallocation	No Demand Reallocation	Full Demand Reallocation
GDP Impact - Illness	-0.27	-0.27	-0.09	-0.09
GDP Impact - Care of Sick	-0.03	-0.03	-0.01	-0.01
GDP Impact - Mortality	-0.25	-0.25	-0.25	-0.25
GDP - Indirect Demand Impact	-0.37	0.00	-0.37	0.00
GDP Impact - Total	**-0.92**	**-0.55**	**-0.72**	**-0.35**
Addendum				
GDP Impact - Work Avoidance	-0.15	-0.15	-0.05	-0.05
GDP Impact With Work Avoidance - Total	-1.07	-0.70	-0.77	-0.40
GDP Impact – Total – United States	-0.91	-0.54	-0.71	-0.34

All of these scenarios could plausibly imply negative growth in the quarter in which the pandemic main wave is concentrated (see Annex E). Strong quarterly growth bounce-backs could be expected once the main wave is over, reflecting both a recovery of output to normal levels as well as overshooting stemming from intertemporal demand reallocations.

In a 1957-type pandemic, GDP impacts range from –0.09 per cent given low absenteeism impacts and full demand reallocation, to –0.34 per cent given high absenteeism impacts and no demand reallocation. In section 4, we estimated that the actual impact of the 1957 pandemic on Canadian GDP was –0.08 per cent.

Table 6.11: 1957 Pandemic Scenario - Aggregate GDP Impacts

	High Absenteeism Impact on Output		Low Absenteeism Impact on Output	
	No Demand Reallocation	Full Demand Reallocation	No Demand Reallocation	Full Demand Reallocation
GDP Impact - Illness	-0.25	-0.25	-0.08	-0.08
GDP Impact - Care of Sick	-0.03	-0.03	-0.01	-0.01
GDP – Indirect Demand Impact	-0.06	0.00	-0.06	0.00
GDP Impact - Total	**-0.34**	**-0.28**	**-0.15**	**-0.09**

6.7 Global Impacts

A pandemic should have impacts on other advanced industrial economies similar to those that we estimate for Canada. Mortality and morbidity rates would not likely vary much across advanced economies, implying similar direct effects. There is no reason to expect significant differences in indirect demand effects. We find identical occupational social density rates in Canada and the United States and these would likely be similar in other advanced economies. Access to and generosity of leave benefits is relatively higher in some European countries, however, even if work-avoidance absenteeism were 50 per cent greater in such countries than in Canada, this would only add 0.1 percentage points to the total GDP impact if absenteeism impacts are high, and 0.03 percentage points if absenteeism impacts are low.

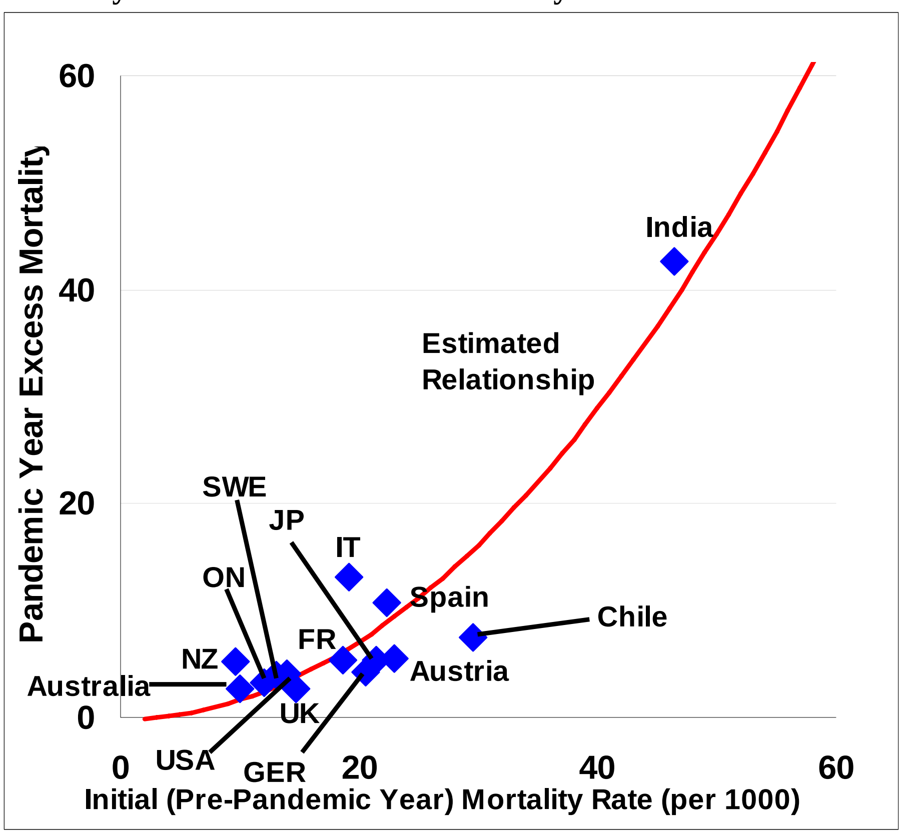
Some studies, however, argue that mortality rates could be significantly higher in emerging economies. For example, McKibbin and Sidorenko (2006) assume, based on differences in per capita health expenditures and the ability to provide antivirals, that a 1918-type pandemic would lead to mortality rates of between 1 and 2 per cent in China, Hong Kong, India, South Korea, Singapore, Thailand and Taiwan, and above 2 per cent in Indonesia, Malaysia and the Philippines. These rates are between 2 and 5 times higher than assumed for the United States. Cooper (2006) argues that China is "poorly equipped to conduct adequate prevention, surveillance, containment, and human-health care" and that "an economic slowdown in China, not to mention Asia as a whole, could cause the commodity boom to bust." The IMF Working Group notes that in 1918 a number of regions of the world experienced mortality rates substantially above that observed in the United States, and that "in some developing countries, limited availability of medical care, overburdened public health facilities, and lack of sanitary infrastructure could cause higher mortality rates than would occur in advance countries today."

The view of the IMF Working Group is certainly plausible, the question is, how much higher? In 1918, advanced economies experienced excess mortality rates of between 0.25 and 0.5 per cent. Davis estimates that excess mortality in India was 4.3 per cent in 1918 and 1 per cent in 1919, 10 to 20 times higher than in advanced economies. Estimates of very high global excess mortality in 1918 are based on the assumption that Indian excess mortality rates prevailed in other less-developed countries.

Would emerging economies be as disproportionately affected today? There is much uncertainty about how a new influenza strain would affect different populations. Variations in 1918 excess mortality were closely related to variations in the pre-pandemic health of respective populations. Figure 6.11 plots the relationship between pandemic year excess mortality and pre-pandemic year all-cause raw mortality for 13 countries plus the province of Ontario. There is a strong statistically significant positive relationship between these measures (regression results are reported in Table D.7 of Annex D). In India, pre-pandemic "normal " mortality was 4.6 per cent, compared with 1.4 per cent in the United States. Spain and Chile, with relatively high base mortality of 2.2 and 2.9 per cent respectively, experienced relatively high excess mortality of 1.1 and 0.8 per cent. Australia and Ontario, with relatively low base mortality of 1 and 1.2 per cent, experienced relatively low excess mortality of 0.27 and 0.33 per cent, respectively.

According to Davis (1951), living conditions in India in the first decades of the twentieth century had improved little from the early 17th century when Pelsaert, a Dutch commercial agent, wrote of "the utter subjection and poverty of the common people, poverty so great and miserable that the life of the people can be depicted or accurately described only as the home of stark want and the dwelling-place of bitter woe."

Figure 6.11: 1918-19 Pandemic: Relationship Between Initial Pre-Pandemic Mortality and Pandemic Excess Mortality



Testimony to the truth of this statement is provided in Table 6.12, which shows life expectancy at birth in selected countries in 2000, as well as in the United States and India prior to the 1918 pandemic. The average life expectancy at birth in India in 1911 was an extraordinarily low 23 years, compared with 50 years in the United States[2]. Life expectancies in today's major emerging economies range between 62.5 in India to 71.4 in China – all significantly greater than in the United States in 1911. Life expectancy in the United States in 1911 was likely longer than in most countries at that time, however, at 50 years it would today rank between Haiti and Gabon.

The notion that Singapore would be disproportionately affected is particularly odd given that Singapore is an advanced economy whose citizens enjoy a life expectancy of 80 years -- the fourth longest on earth, behind only Andorra, San Marino and Japan.

Table 6.12: Life Expectancy at Birth in Selected Countries: 2000 and 1911

Country	Year	Life Expectancy
Japan	2000	80.7
Singapore	2000	80.1
Canada	2000	79.4
Italy	2000	79
France	2000	78.8
United Kingdom	2000	77.7
Germany	2000	77.4
United States	2000	77.1
Taiwan	2000	76.4
South Korea	2000	74.4
China	2000	71.4
Malaysia	2000	70.8
Indonesia	2000	68
Philippines	2000	67.5
Brazil	2000	62.9
India	2000	62.5
Gabon	2000	50.1
United States	**1911**	**50**
Haiti	2000	49.9
Zambia[3]	2000	37.2
India	**1911**	**23**
World	2000	64

While the characteristics of a future pandemic are unknown, the evidence suggests that a pandemic of similar severity to that of 1918 should not lead to excess mortality in emerging economies relative to advanced economies anywhere near the relative impact on India in 1918[4]. Direct economic impacts should therefore also not be much greater than in advanced economies. Workplace avoidance absenteeism would be less likely to occur in emerging economies than in advanced economies owing to the greater

[2] While infant mortality explains part of the difference, Indian life expectancy in 1911 was well below that in the United States at all ages.
[3] Citizens of Zambia had the shortest life expectancy of all countries in 2000, in part because of AIDS.
[4] Significantly larger mortality effects are plausible in countries like Zambia where life expectancy is well below even the advanced country norms of a century ago.

importance of manufacturing and agriculture and less access to various types of leave benefits. Slightly larger direct effects combined with slightly smaller indirect effects mean that the total economic impact on countries like China, India, Brazil, Malaysia and the Philippines should be similar to those in advanced economies. Such impacts would be too brief and small to cause disruptions to global supply chains.

If a severe pandemic were to begin in South Asia, then air travel to that region would likely drop significantly until the pandemic had spread beyond the region (which would occur quickly). Hong Kong and Singapore might see impacts on exports of travel services similar to those during SARS.

6.8 Comparison With Other Studies

Table 6.13 summarizes the GDP impacts[5] estimated by a number of studies for a variety of pandemic scenarios.

Like us, the CBO and McKibbin and Sidorenko examine multiple scenarios. Both the CBO severe and McKibbin and Sidorenko "ultra" scenarios assume population mortality close to double that experienced in the 1918 pandemic. Both also examine mild scenarios similar to 1957 or 1968. Kennedy *et al.* and Bloom, Wit *et al.* both assume mortality rates that lie between the 1957 and 1918 experiences. Jonung and Röger use the CBO severe scenario assumptions in their analysis of impacts on the European Union.

[5] We provide results for studies that, like our own, estimate annual GDP impacts. These should not be confused with the estimates of the present value of future lost earnings in Meltzer, Cox and Fukuda (1999). A present value approach is appropriate to their cost-benefit analysis of interventions, however, this is not the objective of our study. We are primarily concerned with macroeconomic impacts of a pandemic as measured by changes in annual GDP.

Table 6.13: GDP Impacts of Pandemic Scenarios: Comparison of Studies

Study	Scenario Characteristics	Pandemic Year GDP Impacts
This study – 1918 scenario – base case	1918 mortality (0.4 per cent)	Canada: -0.4 to -0.9 per cent; Similar impacts in other advanced economies and in emerging economies
This study – 1918 scenario – with workplace-avoidance absenteeism	1918 mortality (0.4 per cent)	Canada: -0.4 to –1.1 per cent; Similar impacts in other advanced economies and in emerging economies
This study – 1957 scenario	1957 mortality (0.04 per cent)	Canada: -0.1 to -0.3; Similar impacts in other advanced economies and in emerging economies
CBO (1)	Mortality double that of 1918	U.S.: -5 per cent
CBO (2)	1957 mortality	U.S.: - 1.5 per cent
Kennedy *et al.* (Australian Treasury)	Mortality half that of 1918	Australia: -9.3 per cent
McKibbin and Sidorenko (1)	Mortality roughly double that of 1918 in advanced economies	U.S.: -5.5; Canada: -5.7; Japan: -15.8; Europe: -8.0; Singapore: -21.7; Philippines: -37.8; LDCs: -12.2
McKibbin and Sidorenko (2)	1918 mortality	U.S.: -3.0; Canada: -3.1; Japan: -8.36; Europe: -4.3; Singapore: -11.2; Philippines: -19.3; LDCs: -6.3
McKibbin and Sidorenko (3)	1957 mortality	U.S.: -1.4; Canada: -1.5; Japan: -3.3; Europe: -1.9; Singapore: -4.4; Philippines: -7.3; LDCs: -2.4
McKibbin and Sidorenko (4)	1968 mortality	U.S.: -0.6; Canada: -0.7; Japan: -1.0; Europe: -0.7; Singapore: -0.9; Philippines: -1.5; LDCs: -0.69
Bloom, Wit *et al.* (ADB)	Mortality double that of 1957	Asia: -2.6 to -6.8
Jonung and Röger (1)	Same as CBO(1)	E.U.: -1.6

Controlling for scenario differences, the CBO, Kennedy *et al.* and McKibbin and Sidorenko studies estimate significantly higher impacts than we do, while, as will be apparent, Jonung and Röger's estimates are quite similar to ours. To understand the sources of differences it is useful to isolate the mortality and absenteeism components of the estimated GDP impacts. These are provided in Table 6.14. For our study, we show the cases where a high absenteeism impact on output is assumed (elasticity equals 0.6). We show McKibbin and Sidorenko's Canadian estimates.

Table 6.14: Mortality, Morbidity and Absenteeism Assumptions and Associated GDP Impacts

Study	Clinical Attack Rate	Population Mortality Rate	Average Illness Absence (days)	Care of Sick Absenteeism/ Illness Absenteeism	Workplace Avoidance Absenteeism/ Illness Absenteeism	*Estimated Absenteeism and Mortality GDP Impact*
This Study (1918 base case)	25	0.44	7	0.12	0	*-0.6*
This Study (1918 workplace avoidance)	25	0.44	7	0.12	0.65	*-0.7*
This Study (1957)	35	0.04	5	0.12	0	*-0.3*
CBO (1)	30	0.75	7 *	1 *	1 *	*-3.0*
CBO (2)	25	0.03	4	0	0	*-1.0*
Kennedy *et al.* (Australian Treasury)	Not given	0.2	Not given	Not given	Assumed but not given	*-1.5*
McKibbin and Sidorenko (1)	30	near 0	10	0.13	0	*-0.6*
McKibbin and Sidorenko (2)	30	0.1	10	0.13	0	*-0.7*
McKibbin and Sidorenko (3)	30	0.5	10	0.13	0	*-0.8*
McKibbin and Sidorenko (4)	30	1.0	10	0.13	0	*-1.0*
Bloom, Wit *et al.* (ADB)	20	0.1	14	0	0	*-0.3*
Jonung and Röger (1)	30	0.75	7 *	1 *	1 *	*-1.1*

* The CBO assumes that 30 per cent of workers miss 3 weeks of work "either because they were sick, because they feared the risk of infection at work, or because they needed to care for family or friends." The CBO does not explicitly apportion absenteeism among these three categories. We provide here an illustrative equal apportionment.

All the studies assume broadly similar attack rates and average illness durations. If we apply the full set of CBO mortality and absenteeism assumptions to our framework, then we obtain a GDP impact of –1.3 per cent, very close to that of Jonung and Röger. The CBO itself obtains a much larger impact of –3 per cent, largely because it assumes an elasticity of output with respect to the labour input of 1, as opposed to the 0.6 typical in aggregate production functions. The elasticity in cases of temporary absenteeism shocks may be much lower still. Kennedy *et al.* and McKibbin and Sidorenko obtain impacts that are broadly similar to ours given roughly similar scenarios. Both they and Jonung and Röger use full macroeconomic models, however, this methodological choice appears to play little role in determining the absenteeism and mortality impacts. This is not surprising given that we are dealing with largely temporary labour supply shocks whose output effects in a full model would be expected to be similar to those obtained from a production function calculation.

Table 6.15 provides the remaining indirect GDP impact components for each study.

Table 6.15: Decomposition of GDP Impacts

Study	Population Mortality Rate	Estimated Absenteeism and Mortality GDP Impact	Remaining Indirect GDP Impact	Total GDP Impact
This Study (1918 base case)	0.44	-0.6	-0.4	-0.9
This Study (1918 workplace avoidance)	0.44	-0.7	-0.4	-1.1
This Study (1957)	0.04	-0.3	-0.1	-0.4
CBO (1)	0.75	-3.0	-2.0	-5
CBO (2)	0.03	-1.0	-0.5	-1.5
Kennedy *et al.* (Australian Treasury)	0.2	-1.5	-7.8	-9.3
McKibbin and Sidorenko (1)	near 0	-0.6	-0.1	-0.7
McKibbin and Sidorenko (2)	0.1	-0.7	-0.8	-1.5
McKibbin and Sidorenko (3)	0.5	-0.8	-2.3	-3.1
McKibbin and Sidorenko (4)	1.0	-1.0	-4.7	-5.7
Bloom, Wit *et al.* (ADB) (1)	0.1	-0.3	-6.5	-6.8
Bloom, Wit *et al.* (ADB) (2)	0.1	-0.3	-2.3	-2.6
Jonung and Röger (1)	0.75	-1.1	-0.5	-1.6

The CBO's indirect effects stem from psychological demand shocks. In its severe scenario the CBO assumes that demand would fall by 67 per cent for a full quarter in transportation and warehousing, by 80 per cent in arts, recreation, accommodation and food services and by 10 per cent in wholesale and retail trade and manufacturing. This generates a GDP reduction of 2 per cent. In its mild 1957-type scenario the CBO assumes that demand would fall by 17 per cent in transportation and warehousing, by 20 per cent in arts, recreation, accommodation and food services and by 3 per cent in wholesale, retail and manufacturing. This generates a GDP reduction of –0.5 per cent.

Psychological impact assumptions necessarily involve considerable judgement (as the CBO itself rightly notes). Our assumptions are benchmarked to the experience of past pandemics and of SARS. Experience suggests that a pandemic would have little impact on goods transportation and a modest impact on retail sales, with much of any retail impact mitigated by intersectoral and intertemporal reallocations. The CBO's assumed industry impacts are quite large even its mild 1957-1968 scenarios, and do not appear to have occurred during the actual 1957 and 1968 pandemics.

Kennedy *et al.* obtain the largest indirect impact at nearly 8 per cent of GDP. Three percentage points of this stem from assumed confidence impacts on consumption, which they claim would be particularly acute in recreation, tourism and travel-related services. We agree that the latter sectors would likely be significantly affected, and incorporate such assumptions in our own estimates, however, three months of value-added in arts, entertainment and recreation and air transportation passenger services equals only 0.26 per cent of Canadian GDP. An additional 2½ percentage of their indirect impact stems from investment reductions resulting from firms needing "to adjust to an environment where they held too much capital (or at least the wrong type of capital) compared with the number of workers." In a neoclassical growth model, the permanent effect of mortality on labour supply would eventually lead to an equivalent impact on the capital stock, however, this would be a drawn-out process that would not involve a sharp decline in investment in the pandemic year. In an endogenous growth model where capital deepening is the driver of long-run growth, investment need not be adversely affected. Brainerd and Siegler (2002) find support for such a capital deepening channel in their study of U.S. state growth rates in the 12 years following the 1918 pandemic. The labour supply reduction stemming from absenteeism should have no impact on investment, as it would be known to be temporary and therefore would have no effect on the expected future marginal product of capital.

For Canada, the demand component of McKibbin and Sidorenko's indirect effect is –0.6 per cent, close to our own estimate of –0.4 per cent. Most of their large total indirect effect stems from an entirely different channel, namely a large assumed increase in business costs. This channel is described in McKibbin and Lee as the cost of disease prevention in affected industries, which in the case of SARS they assume represented a 5 per cent increase in total costs in affected service industries in Hong Kong and China. In their severe 1918 scenario, McKibbin and Sidorenko scale these cost shocks by their assumed mortality shocks. This leads them to impose an annual total economy cost shock of more than 12 per cent for Hong Kong, between 2 and 4 per cent for many emerging economies and between 1 and 2 per cent for advanced economies.

We find this channel puzzling. McKibbin and Sidorenko do not provide any evidence that SARS ever generated such cost shocks, and there is no evidence of them in macroeconomic data. Countries would not be able to prevent the transmission of a phase-six influenza pandemic across or within their borders, so it is hardly likely that firms could do so within their workplaces (or would try to do so). Firms might take measures to slow transmission among staff, although the efficacy of this could be limited. The IMF working group suggests a number of possible measures such as purchasing an advance supply of facemasks, antiseptic wipes, gels and towels and more frequent cleaning of desks, phones, keyboards, railing and counters. While such measures would provide a boost to producers of antiseptic gels and similar products[6], it is difficult to believe that they would have any macroeconomic effect.

The large indirect effects of Bloom, Wit *et al.* stem entirely from large assumed consumption impacts.

Our indirect effects are very close to those of Jonung and Röger, who note the importance of expenditure reallocations in mitigating annual aggregate impacts.

[6] Such measures were tried in 1918. The *Toronto Star* of Oct 12, 1918 reported: "That Toronto people believe in prevention rather than cure seems to be the case, for the amount of disinfectants and germicides sold since the breaking out of the disease in the city has been tremendous, although there is no way of ascertaining the exact quantities sold. Factories which employ large numbers of men and women are taking extreme measures, and are using liquid disinfectants in the rooms to prevent the spread of the disease. Wholesale drug companies also report large sales of camphor to retail druggists, some of which say that as many as seven and eight pounds of it are sold in one day."

The IMF Working Group, McKibbin and Sidorenko and Kennedy *et al.* argue that a pandemic would have notable effects on risk premia and asset prices. However, as Jonung and Röger note, no such effects were apparent in past pandemics. A pandemic would be a short-lasting event that would be known to be temporary. It would not affect physical capital, infrastructure or economic institutions. Such a shock should not affect asset prices, which should reflect the expected returns on an asset over a long horizon. If effects did occur, they would be very brief and unlikely to have macroeconomic consequences.

7 Conclusions

The 1918 influenza pandemic was more severe than any for which we have reliable data. Declines in U.S. industrial production in the fall of 1918 suggest that the pandemic reduced annual 1918 U.S. GDP by up to 0.5 per cent. Small impacts are apparent in passenger rail and transit use. Retail sales, external trade, financial markets and bankruptcies appear to have been unaffected. The relatively mild 1957 and 1968 pandemics appeared to have very small economic impacts. While economies have changed significantly since 1918, these changes are not a convincing basis for concluding that impacts today would be significantly greater than in 1918.

Some conclude from the experience of SARS that a pandemic today would have much larger economic impacts. However, the effect of SARS was limited to significant but temporary reductions in air travel to affected locations. Hong Kong and Singapore were particularly vulnerable owing to the importance of tourism to their economies. Air travel reductions stemming from SARS and the start of the second Gulf War caused Hong Kong and Singapore GDP to contract in the second quarter of 2003, however, goods trade and retail sales were largely unaffected. Reduced air travel also affected Canada, with negative impacts on the accommodation industry, particularly in Toronto. However, travel and accommodation impacts reduced Canadian annual GDP by only about 0.03 per cent in 2003.

Our analysis suggests that a severe pandemic like that of 1918 would reduce annual GDP by about 1 per cent a result of higher worker absenteeism and reduced spending in some sectors. Expenditure reallocations across sectors and across time would mitigate the impact of the latter on total annual GDP growth. Growth could be expected to rebound sharply immediately following the pandemic as absenteeism returned to normal levels and spending occurred that had been delayed. A mild pandemic like those of 1957 and 1968 would likely have very small economic impacts.

Some argue that a severe pandemic would lead to high rates of absenteeism as workers avoid their workplaces in order to escape infection. There is no evidence that such absenteeism was significant during past pandemics or during SARS. To estimate an upper bound to possible workplace avoidance absenteeism we develop a model that takes into account the importance of socially dense occupations, the actual dynamic characteristics of the pandemic, its plausible effects on the perceived vulnerability of the population in and out of the workplace, and the costs of extended leave. Estimates from this model suggest that peak workplace avoidance absenteeism would not be sufficient to cause breakdowns in goods transportation, disrupt supply chains and payments and clearing systems, or cause breakdowns of public utilities.

Our results are consistent with the broader findings of Albala-Bertrand who examines 28 other natural disasters in 26 countries and finds that the short and long-run aggregate economic effects are generally much smaller than initially predicted. Effects are small because human societies are extraordinarily adaptable. For almost every direct negative effect there is a potential offsetting response, including economy-wide, sectoral, household and individual reactions that mitigate the disaster by increasing supplies and changing technologies.

Albala-Bertrand notes that natural disasters usually engender predictions of large negative economic effects, and in particular, large indirect effects. *Ex post*, effects usually prove small and indirect effects are indiscernible, however, "standing views go largely unchallenged and appear to have a life of their own." They reflect a view of disasters that "…rarely consider the response to disaster impacts as part of the same event – as if society functioned without in-built reactive mechanisms." In fact, "the final outcome of a disaster situation is the net effect of largely negative impact effects and generally positive response effects."

Those studies that predict that a pandemic would have large negative impacts usually do so because they assume that large indirect effects would result from fear of the disease and consequent efforts by individuals to avoid infection. Fear is hard to measure, but we can measure how people respond to stressful situations. It is likely that people would be fearful during a 1918-type pandemic, just as they likely were in 1918. Some studies seem to assume that fear by definition implies widespread behavioural changes, with economies breaking down as people become dysfunctional from fear of infection.

There is ample evidence that people do not respond to fear in this way. An emerging literature that merges insights from psychology and economics suggests that people engage in strategies to effectively manage fear and avoid becoming paralysed by it. Furthermore, it is not absolute risk that determines behaviour, but rather the perceived relative risk and cost of a particular behaviour relative to an alternative. Perceived relative risks may be much smaller than absolute risks, particularly if a risk is pervasive.

If a pandemic were to occur, human suffering and loss of life would outweigh economic concerns. GDP impacts are not necessarily the best measure of the effects on people of a virus or other natural disaster.

Annex A – Reconstruction of 1918 Morbidity Rates

A.1 Summary of the Approach

Our approach relies on a number of data sources. We have data on daily influenza and pneumonia case incidence and deaths for the Great Lakes Illinois naval station. This was the largest naval training station with an average complement of 45,000, and seems quite representative. We have weekly influenza and pneumonia death rate data for Boston and number of other U.S. cities. We have monthly influenza and pneumonia death rate data for the entire United States.

To reconstruct morbidity rates we first calibrate a hazard model that replicates observed Illinois naval station daily mortality rates given observed daily new case incidence rates and an assumed average duration of illness. This model generates a daily morbidity path for the Illinois naval station. We then demonstrate that the Illinois naval station new case incidence rate path can be modelled as a gamma distribution. We calibrate a gamma distribution new case incidence path for Boston, that, when fed into the previously calibrated hazard model generates a mortality rate path that conforms to the observed weekly mortality path for Boston. As a by-product, this model generates a daily morbidity path for Boston. Given the observed speed of the mortality surge from the East coast to the West coast, we construct a U.S. aggregate daily morbidity rate path as a moving average of the Boston morbidity path. We verify that the model-generated monthly U.S. mortality path matches the observed monthly U.S. excess mortality.

A.2 The Hazard Model

For each person who has been sick for t days the probability of recovering at the end of the day is p^{well} and the probability of dying at the end of the day is p_t^{die}.

We calibrate p^{well} so that the average duration of illnesses that end in recovery is 7 days. This implies p^{well} =0.143.

p_t^{die} is assumed to have the form:

$$p_t^{die} = \beta \cdot f(t, \mu, \sigma) \cdot g(t)$$

where f is the cumulative normal distribution, β is a scalar and g has the form:

$$g(t) = \begin{cases} 1; t \le \bar{t} \\ \rho^{t-\bar{t}}; t \ge \bar{t} \end{cases}$$

If the first case in a given location occurs in period 1, then the morbidity (stock) rate at that location at the beginning of time T is:

$$m_T = \sum_{t=1}^{T} i_t \prod_{s=1}^{T-t-1} (1 - p^{well} - p_s^{die})$$

where i_t is the location's case incidence rate at the beginning of period t. The location's death (flow) rate at the end of time T is:

$$D_T = p_{T-t}^{die} \cdot \prod_{s=1}^{T-t-1} (1 - p^{well} - p_s^{die})$$

The fitted new case incidence rate for the location has the form:

$$\hat{i}_t = \frac{\theta}{\lambda^{\alpha}\Gamma(\alpha)} t^{\alpha-1} e^{-\frac{t}{\lambda}}$$

For the Great Lakes Illinois Naval Station calibrating to the actual daily new case incidence rate yields θ = 21.5, α = 8 and λ = 1.3. Given this calibrated new case incidence rate, β, μ, σ, ρ and $\bar{t}$ are then chosen so that dynamic simulated death rate closely matches the observed death rate. This implies β = 0.037, μ = 4.5, σ = 0.3, ρ = 0.8 and $\bar{t}$ = 8. The resulting calibrated new case incidence and simulated death rate paths are shown in Figures A.1 and A.2.

Figure A.1

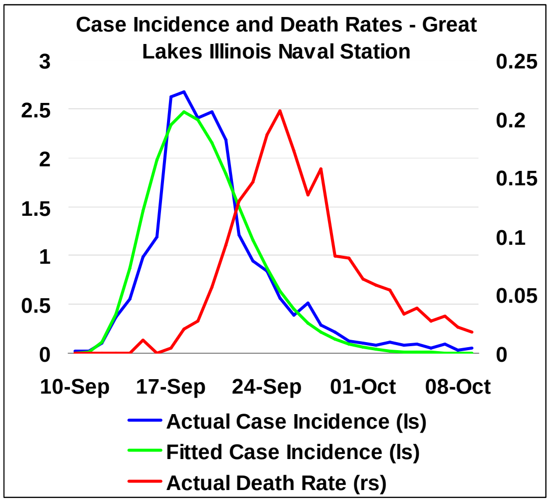
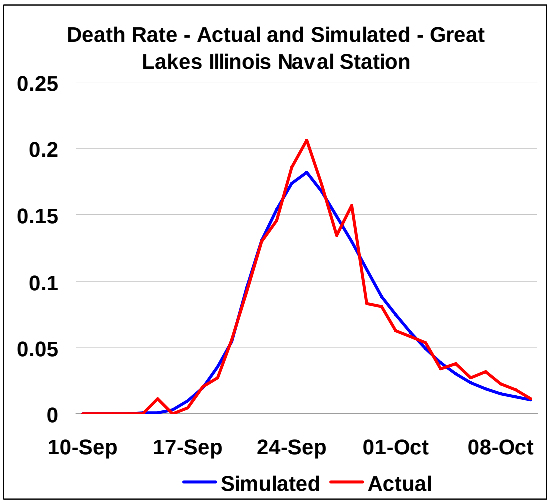


Figure A.2



Using this death probability parameterization we then calibrate a gamma distribution for the new case incidence path of the city of Boston (Figure A.3) that, when applied to the hazard model yields a weekly death rate path that closely matches the observed path for

Boston (figure A.4). The new case incidence parameterization for Boston is $\theta = 17.2$, $\alpha = 5.1$ and $\lambda = 4.1$.

Figure A.3

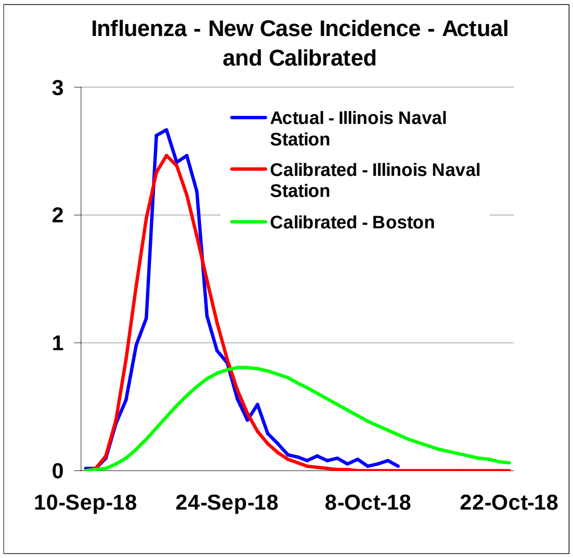
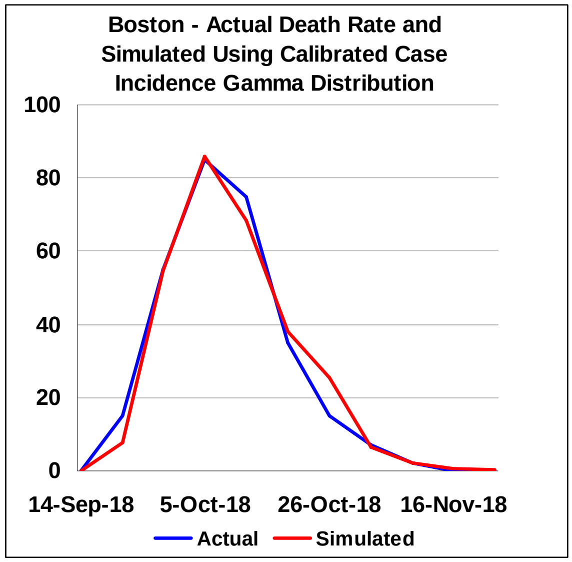


Figure A.4

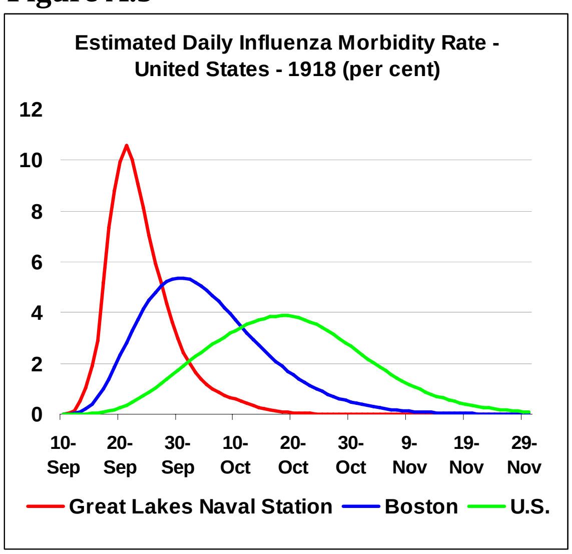


Since the peak of the first wave took about 30 days to penetrate the entire United States, we model the national morbidity path at time k, m_k^N, as a 30-day moving average of the initial Boston path m^I:

$$m_k^N = \sum_{T=k-30}^{k} m_T^I = \sum_{T=k-30}^{k} \sum_{t=1}^{T} i_t^I \prod_{s=1}^{T-t-1} (1 - p^{well} - p_s^{die})$$

The resulting morbidity paths are shown in Figure A.5.

Figure A.5



Annex B – Estimating Daily Morbidity Rates – 1957 Pandemic

We know monthly excess illness absenteeism for Canada in 1957 and 1958. We replicate this monthly pattern by specifying daily single city new case incidence as the sum of two gamma distributions:

$$\hat{i}_t = g(t) + h(t)$$

$$g(t) = \frac{\theta_1}{\lambda^{\alpha_1}\Gamma(\alpha_1)} t^{\alpha_1 - 1} e^{-\frac{t}{\lambda_1}}$$

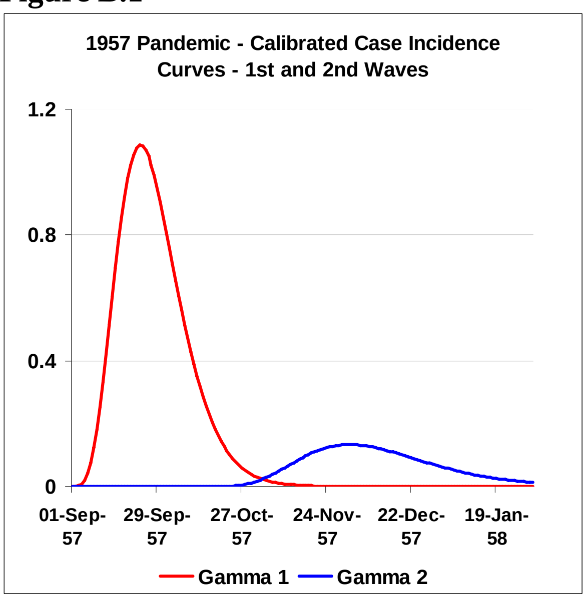
$$h(t) = \begin{cases} 0; t < \bar{t} \\ \dfrac{\theta_2}{\lambda^{\alpha_2}\Gamma(\alpha_2)} (t - \bar{t})^{\alpha_2 - 1} e^{-\frac{(t-\bar{t})}{\lambda_2}}; t \geq \bar{t} \end{cases}$$

where the first distribution represents the initial main wave and the second distribution the second wave. The values of the calibrated parameters are shown in Table B.1 and the resulting case incidence curves in Figure B.1.

Table B.1

i	θ_i	α_i	λ_i
1	28	6.3	4.4
2	7	6.3	9

Figure B.1



We calibrate p^{well} so that the average duration of illnesses that end in recovery is 5 days. This implies p^{well} =0.2.

p_t^{die} is again assumed to have the form:

$$p_t^{die} = \beta \cdot f(t, \mu, \sigma) \cdot g(t)$$

where f is the cumulative normal distribution, β is a scalar and g has the form:

$$g(t) = \begin{cases} 1; t \leq \bar{t} \\ \rho^{t-\bar{t}}; t \geq \bar{t} \end{cases}$$

Given the calibrated new case incidence rate, β, μ, σ, ρ and $\bar{t}$ are then chosen so that dynamic simulated death rate generated by the hazard model closely matches the observed death rate. This implies β = 0.013, μ = 4.5, σ = 0.3, ρ = 0.8 and $\bar{t}$ = 4.

Dynamic simulation of the hazard model yields the single city and Canadian daily morbidity paths shown in Figure B.2. Actual and simulated monthly Canadian morbidity is shown in Figure B.3.

Figure B.2

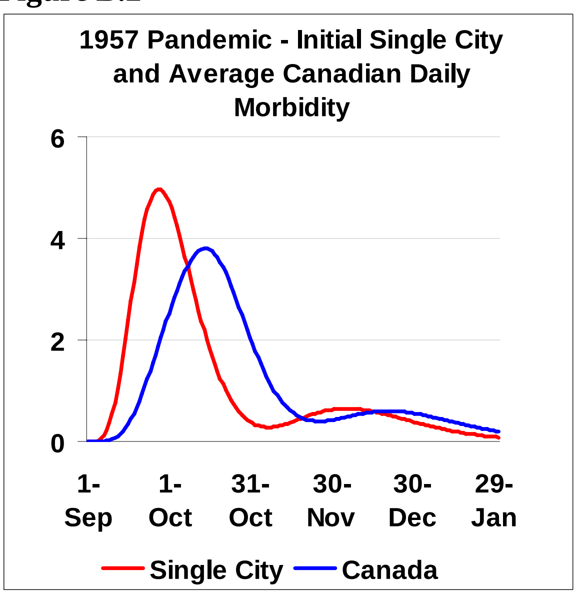
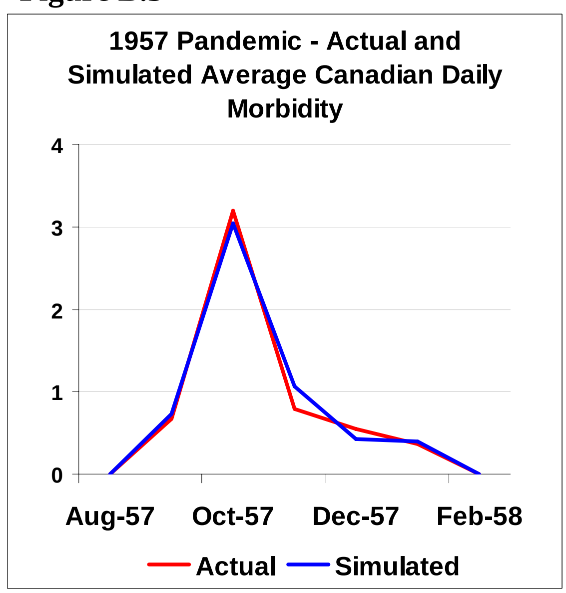


Figure B.3



Annex C – Modelling Workplace-Avoidance Absenteeism

We assume that a fraction γ of those in socially-dense occupations regard being in the workplace as riskier than alternatives such as staying at home, and believe that their ultimate probability of contracting the disease would be lowered by being absent from the workplace at some point. The fraction γ is not the proportion of those in socially dense occupations *actually* absent because of workplace avoidance at any one point in time. Rather, it represents those that believe that some workplace avoidance for some period during the pandemic could reduce their ultimate risk of infection. We refer to this as the "vulnerable population". Those in this group can be modelled as minimizing a loss function:

$$\min_{T_1, T_2} \left[\int_0^{T_1} E(m_t) d_t + \int_{T_1}^{T_2} \psi E(m_t) d_t + \int_{T_2}^{\bar{T}} E(m_t) d_t + c(T_2 - T_1) \right]$$

where T_1 is the absenteeism starting point, T_2 is the absenteeism ending point, $E(m_t)$ is the expected morbidity path in the workplace, ψ is a scalar ($0 \leq \psi < 1$) that represents the perceived risk reduction obtained by workplace avoidance, and c is the cost of leave, where $c'(.) > 0$ and $c''(.) \geq 0$, reflecting the fact that the level and marginal cost of leave increase with the duration of leave.

The solution to this problem is:

$$(1-\psi)E(m_{T_2}) + \frac{\partial c(T_2 - T_1)}{\partial T_2} = 0$$

$$(1-\psi)E(m_{T_1}) - \frac{\partial c(T_2 - T_1)}{\partial T_1} = 0$$

The first of these equations equates the marginal benefit of continuing an absence at time T2 with the marginal cost of doing so given that the absence began at time T1. The second equation equates the marginal benefit of starting an absence at time T1 with the marginal cost of doing so given that the absence ends at time T2.

For example, if $c = (T_2 - T_1)^{\beta}$, ($\beta \geq 1$), then the solution will be characterized by:

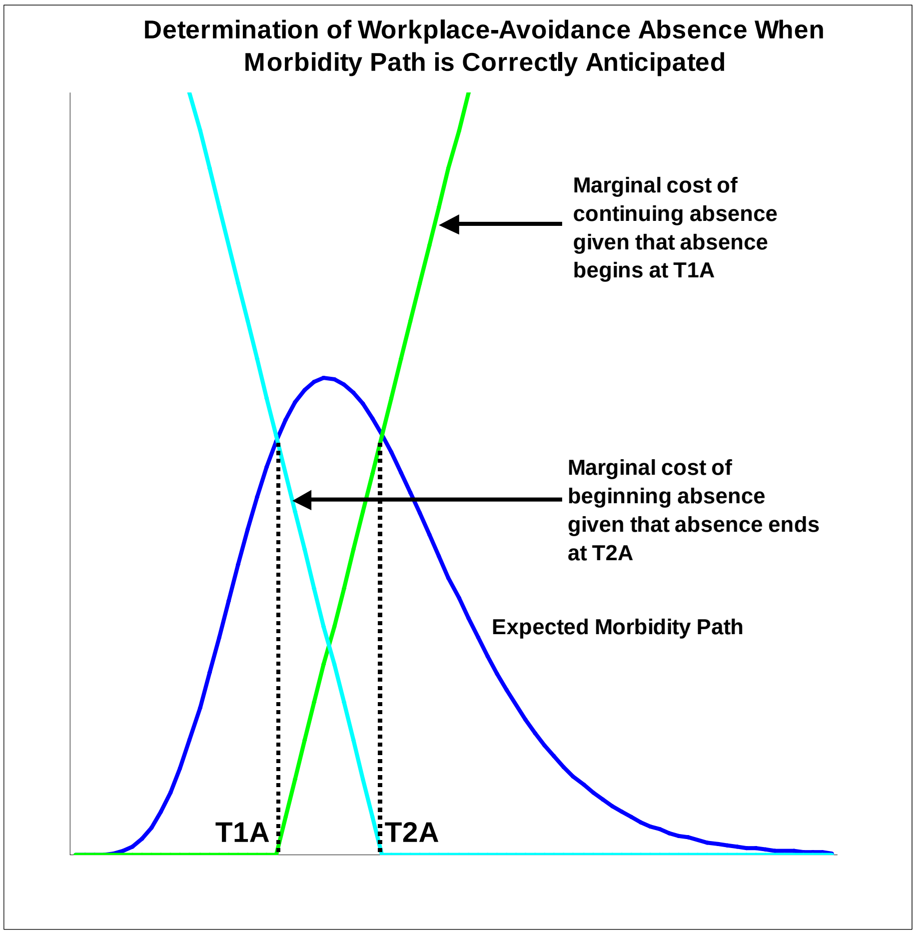
$$E(m_{T_2}) = E(m_{T_1})$$

$$T_2 - T_1 = \frac{\left[(1-\psi)E(m_{T_2})\right]^{\frac{1}{\beta-1}}}{\beta} = \frac{\left[(1-\psi)E(m_{T_1})\right]^{\frac{1}{\beta-1}}}{\beta}$$

The desired absence duration will be decreasing in the cost of leave and increasing in the perceived risk of the workplace relative to alternatives. The expected mid-point of the workplace-avoidance absence path will be close to the expected workplace morbidity peak given a fairly symmetric expected morbidity path. Those that begin a workplace-avoidance absence earlier in the pandemic are thus likely to plan on a longer absence than those that begin later.

Figure C.1 demonstrates the choice of absence when the morbidity path is correctly anticipated.

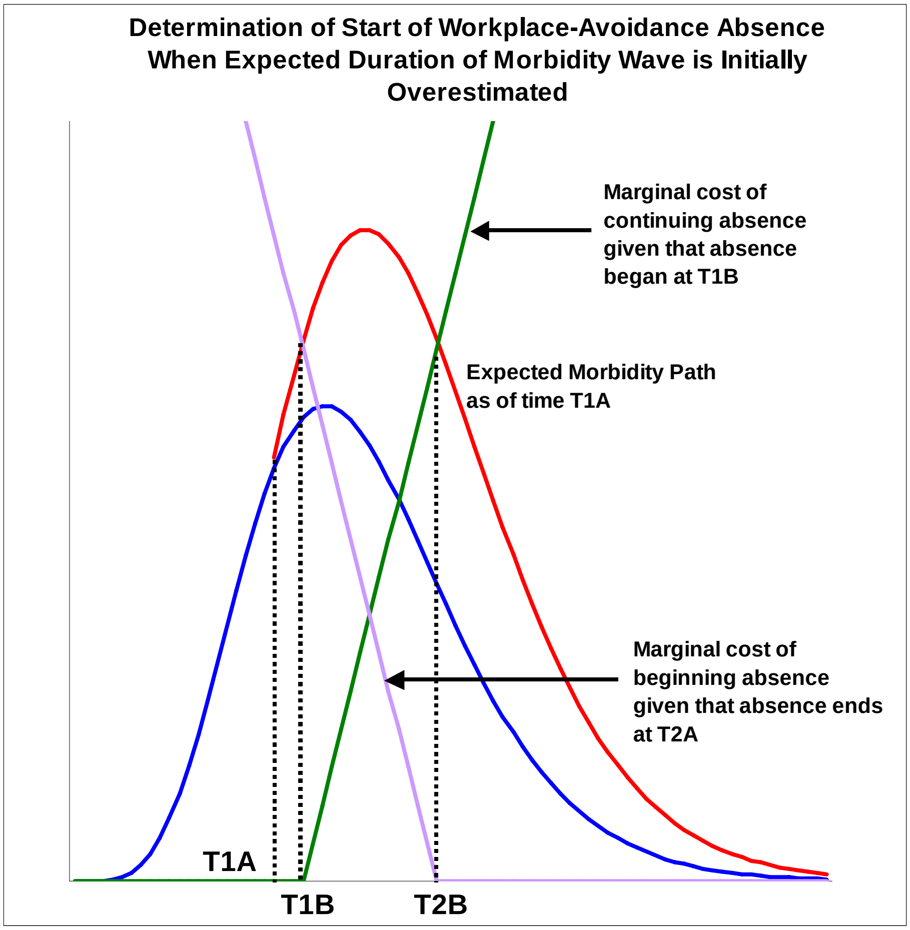
Figure C.1



The absence begins at T1A and ends at T1B, and is closely centred around the morbidity peak.

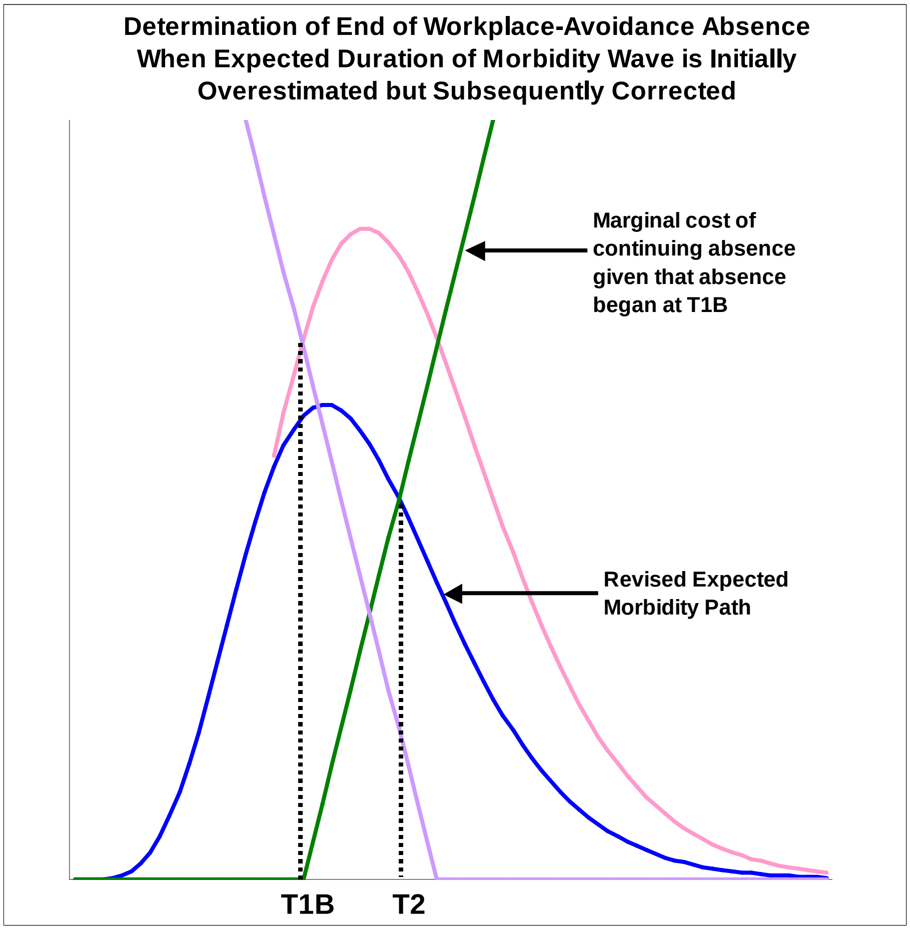
Figure C.2 shows the case where at time T1A the morbidity path is expected to be longer and more severe (given by the red line) than ultimately proves to be the case. The absence then begins later, at T1B, and is expected to end at T2B, centred around the peak of this more pessimistic expected morbidity path.

Figure C.2



If, however, the individual learns the true path between time T1B and T2B, then the end point of the absence shifts earlier to time T2 as shown in Figure C.3, as this equates the marginal benefit of continuing the absence with the marginal cost of doing so given that the absence began at T1B.

Figure C.3



The incidence of new workplace avoidance absences in this case will lag the true new illness case incidence path.

We do not know the true values of the relevant parameters, nor their distribution, nevertheless, this framework provides a useful qualitative benchmark for modelling the possible path of workplace avoidance absenteeism during a pandemic and determining the sensitivity of the estimated path to alternative assumptions.

We assume that new workplace avoidance incidence f is proportional to either coincident or lagging new illness incidence:

$$f_t = \Omega i_{t-L}$$

where Ω is determined by the fact that the cumulative incidence rate is by definition 1 for those who do not exit the vulnerable group:

$$\int_0^\infty f_t dt = 1$$

Consistent with the results of our loss-minimization model we assume that the expected duration of an absence spell is greater the earlier the absence begins. We assume that the expected duration of such spells ranges between D^{min} and D^{max} where D^{max} is the expected duration of a spell that begins on the first day of local illness incidence and D^{min} is the expected duration of spells that begin on or after the morbidity peak (see Figure C.4). If everyone knew the exact future morbidity path in advance then no spells would begin after the morbidity peak. In reality, the future path will not be known with certainty and workplace-specific peaks will vary and will be distributed around the local peak.

Figure C.4

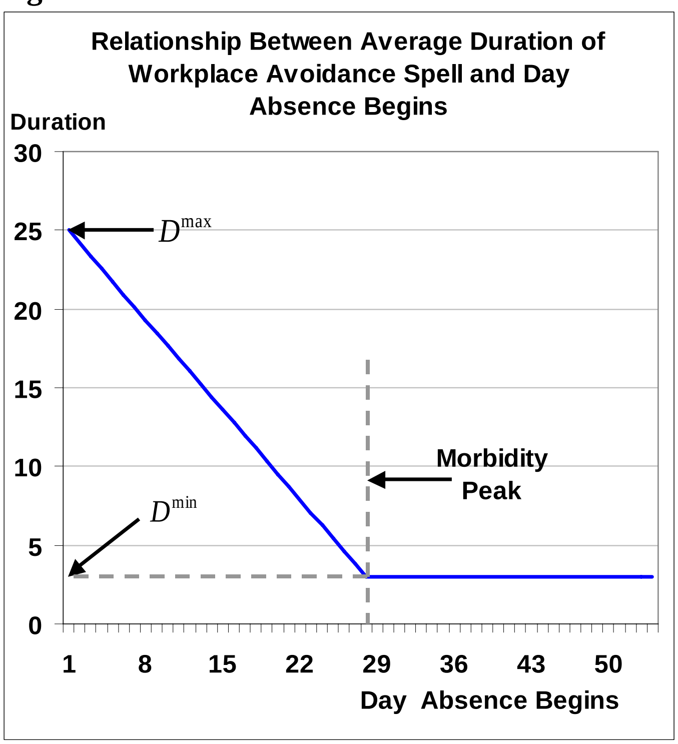
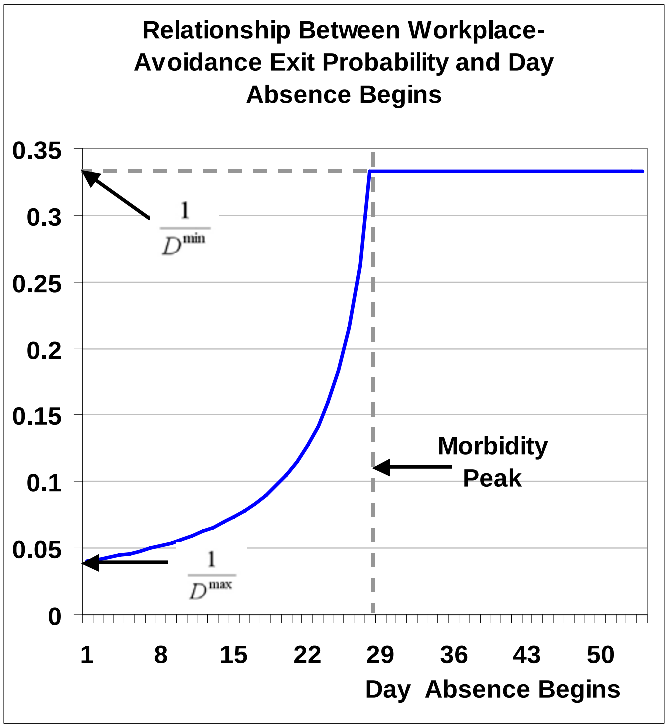


Figure C.5 shows how the probability of a planned exit from a workplace avoidance spell varies according to when in the course of the local wave the absence began. It illustrates a scenario where D^{max} = 25 days and D^{min} = 3 days.

Figure C.5



The proportion of the vulnerable population that is absent by reason of work avoidance at a given point in time is denoted by s and has the form:

$$s_T = \sum_{t=1}^{T} f_t \cdot (1 - p_t^{exit})^{T-t}$$

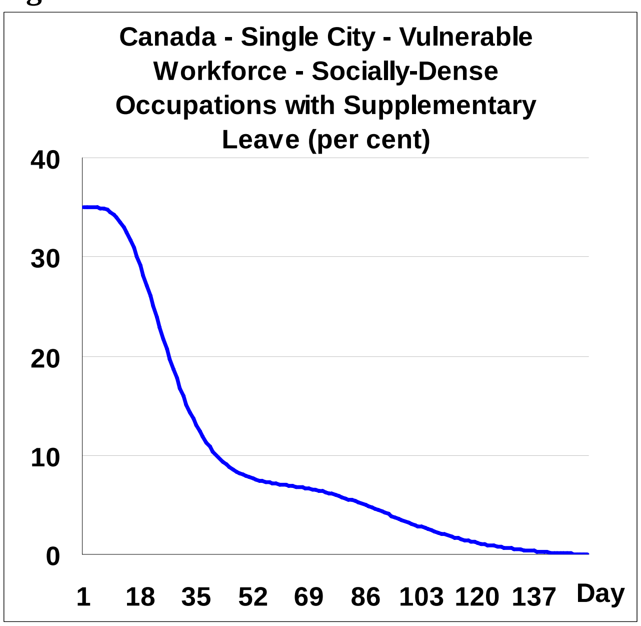
The vulnerable population itself will not be fixed in time. Persons can exit the vulnerable population in two ways, either by actually becoming clinically ill with influenza and recovering, or by living in a household in which someone has contracted influenza. The first group will have acquired immunity and would thus not fear again contracting the disease. The second group would regard the workplace as less risky than being at home, and would likely have a diminished view of the efficacy of any risk-avoidance measure in ultimately avoiding infection. To some degree, this would also be true of anyone who becomes involved in daily visits to assist close family members or friends who are not a member of the person's immediate household. Many, of course would be in such close contact but appear to never have contracted the illness. In reality, they would have done so, but would have been asymptomatic. Some might actually have been immune (as may have been the case for older persons in 1918). Regardless, perceived absolute risk will fall as the person begins to believe that he or she is immune and the perceived risk of the workplace relative to the home disappears.

All those in the vulnerable group are assumed to ultimately exit it because of either recovery from illness or close proximity with clinically ill persons by the end of the local main wave. Incidence of high proximity outside the workplace is coincident with case incidence, thus the vulnerable population evolves according to:

$$\gamma_T = \left(1 - \frac{\int_0^T i_t dt}{\int_0^\infty i_t dt} \right) \bar{\gamma}$$

where $\bar{\gamma}$ is the initial proportion of the socially dense workforce that is vulnerable. Figure C.6 illustrates the evolution of the vulnerable group as a share of the total workforce in a case where all those in socially dense occupations are initially in the group and local case incidence follows the path estimated for the 1957 pandemic.

Figure C.6



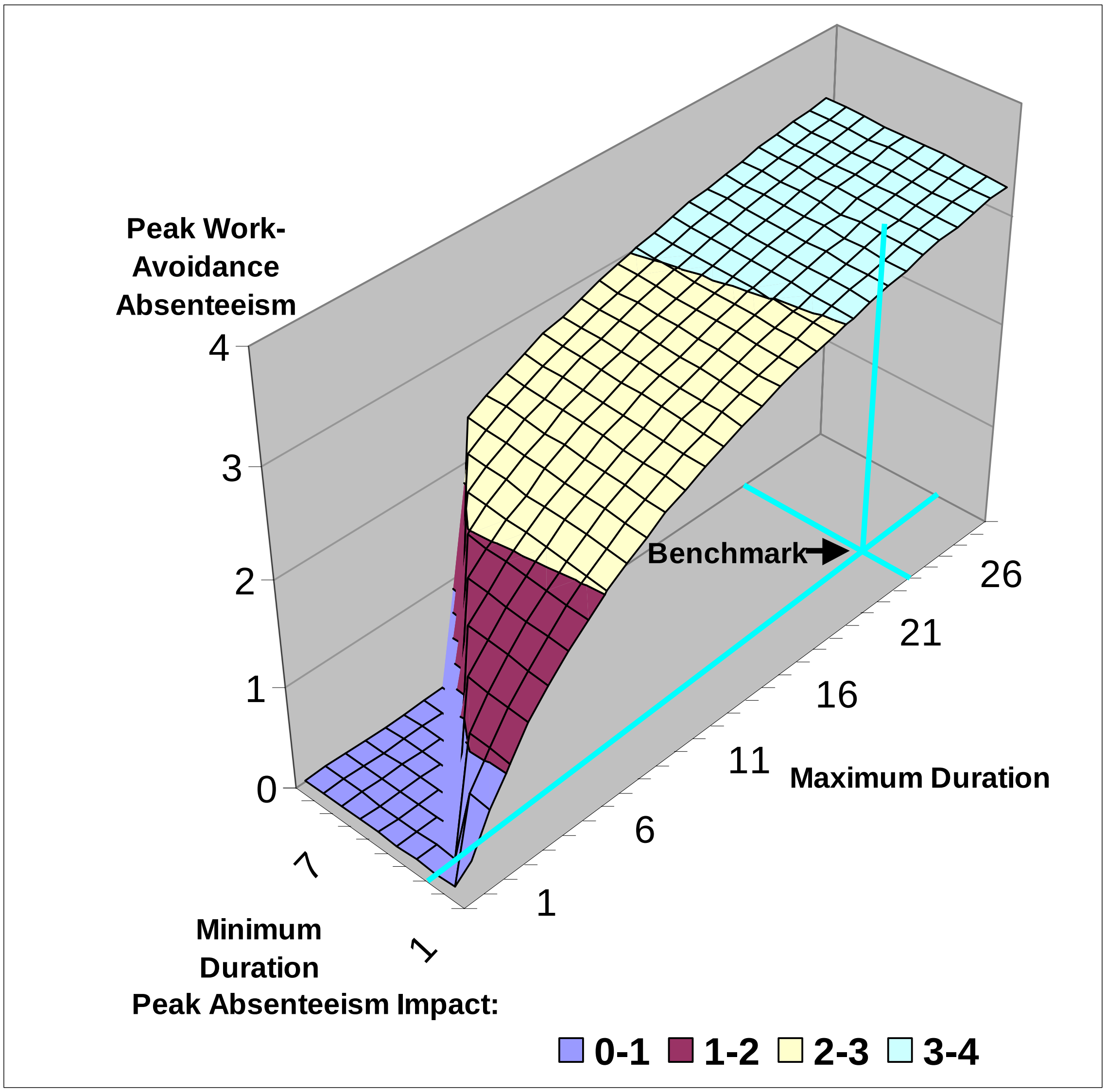
If δ is the proportion of the workforce in socially-dense occupations then the total workplace-avoidance absenteeism rate will be:

$$\delta \gamma_T s_T = \delta \left(1 - \frac{\int_0^T i_t dt}{\int_0^\infty i_t dt} \right) \bar{\gamma} \sum_{t=1}^{T} f_t \cdot (1 - p_t^{exit})^{T-t}$$

In socially dense occupations workplace-avoidance absenteeism will be $\gamma_T s_T$.

Figure C.7 shows how peak daily workplace avoidance varies depending on the choice of maximum and minimum absence durations. These peaks are highly robust to more pessimistic choices than those assumed in our simulations.

Figure C.7: Peak All-Firm Workplace-Avoidance Absenteeism as a Function of Maximum and Minimum Durations of Absence



Annex D - Detailed Derivations and Econometric Results

Table D.1: 1918 Scenario: Derivation of Mortality Impact on GDP

Age	0-14	15-19	20-24	25-34	35-44	45-54	55-64	65+	Total
1918 – U.S. Excess Mortality (per 100,000)	485	450	650	950	475	220	140	60	437
Implied % Change in Labour Force	NA	-0.45	-0.65	-0.95	-0.48	-0.22	-0.14	-0.06	-0.43
Implied % Change in GDP									**-0.26**

Table D.2: 1918 Scenario: Derivation of Morbidity Impact on GDP

Age	0-14	15-19	20-24	25-34	35-44	45-54	55-64	65+	Total
1918 – Baltimore Cases (per 1000)	290	240	230	240	160	110	90	65	200*
Assumed Cases (per 1000) (= 1918 Baltimore *1.4)	406	336	322	336	224	154	126	91	250**
Implied % Change in Hours	NA	-0.72	-0.69	-0.72	-0.48	-0.33	-0.27	-0.20	-0.45
Implied % Change in GDP – High									**-0.27**
Implied % Change in GDP – Low									**-0.09**
*1920 U.S. Pop. Distribution **2004 Canadian Pop. Distribution									

TableD.3: 1957 Scenario: Derivation of Morbidity Impact on GDP

Age	0-14	15-19	20-24	25-34	35-44	45-54	55-64	65+	Total
1957 – Kansas City Cases (per 1000)	425	525	400	250	250	200	200	150	308
Assumed Cases (per 1000) (= 1957 Kansas City *1.15)	489	604	460	289	289	230	230	340	348
Implied % Change in Hours									-0.42
Implied % Change in GDP – High									**-0.25**
Implied % Change in GDP – Low									**-0.08**

Table D.4: Regression of U.S. Real GNP Growth on Index of Industrial Production Growth (1910-1929)

R Square	0.43					
Adjusted R Square	0.40					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.03	0.01	4.87	0.000	0.02	0.04
dln(Ind prod)	0.26	0.07	3.69	0.002	0.11	0.41

Table D.5: Regression of Monthly Canadian Personal/Family Absentee Rate on Illness and Disability Absentee Rate (1st differences; January 1976-December 2004)

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.00	0.00	0.90	0.37	0.00	0.01
Illness Absentee Rate (1st difference)	0.12	0.02	7.30	0.00	0.09	0.16

Table D.6: Regression of Industry Coefficients from Table 6.3 on Social Density and Unionization Rate Variables

Regression Statistics				
Multiple R Square	0.718			
R Square	0.515			
Adjusted R Square	0.434			
Standard Error	0.243			
Observations	15			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	1.373	0.146	9.402	0.000
Ln(1-Social Density)	0.518	0.176	2.945	0.012
Ln(Unionization)	0.222	0.079	2.804	0.016

Table D.7: Regression of 1918-19 Pandemic Year Excess Mortality on Pre-Pandemic Year Mortality (14 Countries)

Multiple R	0.934			
R Square	0.872			
Adjusted R Square	0.861			
Standard Error	3.842			
Observations	14			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-0.193	1.393	-0.138	0.892
Pre-Pandemic Mortality Rate (Squared)	0.018	0.002	9.044	0.000

Table D.8: 1918 Scenario – No Demand Reallocation; High Absenteeism Impact on Output – Monthly and Quarterly GDP Impacts - Main Wave Peak in February, Second Wave Peak in April

	Illness and Care of Sick	Mortality	Psychological Demand	**Total (No Workplace Avoidance)**	Workplace Avoidance	Total (With Workplace Avoidance)
% Level Impact						
January	-0.27	-0.02	-0.33	**-0.62**	-0.19	-0.81
February	-2.16	-0.19	-2.60	**-4.95**	-1.24	-6.19
March	-0.75	-0.25	-0.90	**-1.90**	-0.31	-2.21
April	-0.33	-0.28	-0.40	**-1.01**	-0.05	-1.05
May	-0.15	-0.29	-0.18	**-0.62**	-0.01	-0.63
June	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
July	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
August	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
September	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
October	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
November	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
December	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
% Level Impact						
Q1	-1.06	-0.16	-1.28	**-2.49**	-0.58	-3.07
Q2	-0.16	-0.29	-0.19	**-0.64**	-0.02	-0.66
Q3	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
Q4	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
Year 1	**-0.30**	**-0.26**	**-0.37**	**-0.93**	**-0.15**	**-1.08**
Year 2	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
*p.p. Growth Impact**						
Q1	-1.06	-0.16	-1.28	**-2.49**	-0.58	-3.07
Q2	0.90	-0.13	1.08	**1.85**	0.56	2.41
Q3	0.16	0.00	0.19	**0.35**	0.02	0.37
Q4	0.00	0.00	0.00	**0.00**	0.00	0.00

*quarterly rates

Table D.9: 1918 Scenario – Full Demand Reallocation; Low Absenteeism Impact on Output – Monthly and Quarterly GDP Impacts - Main Wave Peak in February, Second Wave Peak in April

	Illness and Care of Sick	Mortality	Psychological Demand	**Total (No Workplace Avoidance)**	Workplace Avoidance	Total (With Workplace Avoidance)
% Level Impact						
January	-0.09	-0.02	-0.16	**-0.28**	-0.06	-0.34
February	-0.72	-0.19	-1.14	**-2.05**	-0.41	-2.46
March	-0.25	-0.25	0.85	**0.35**	-0.10	0.24
April	-0.11	-0.28	0.25	**-0.14**	-0.02	-0.15
May	-0.05	-0.29	0.11	**-0.23**	0.00	-0.24
June	0.00	-0.29	0.09	**-0.20**	0.00	-0.20
July	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
August	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
September	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
October	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
November	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
December	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
% Level Impact						
Q1	-0.35	-0.16	-0.15	**-0.66**	-0.19	-0.85
Q2	-0.05	-0.29	0.15	**-0.19**	-0.01	-0.20
Q3	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
Q4	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
Year 1	**-0.10**	**-0.26**	**0.00**	**-0.36**	**-0.05**	**-0.41**
Year 2	0.00	-0.29	0.00	**-0.29**	0.00	-0.29
*p.p. Growth Impact**						
Q1	-0.35	-0.16	-0.15	**-0.66**	-0.19	-0.85
Q2	0.30	-0.13	0.30	**0.47**	0.19	0.66
Q3	0.05	0.00	-0.15	**-0.10**	0.01	-0.09
Q4	0.00	0.00	0.00	**0.00**	0.00	0.00

*quarterly rates

Table D.10: 1957 Scenario – No Demand Reallocation; High Absenteeism Impact on Output – Monthly and Quarterly GDP Impacts - Main Wave Peak in February, Second Wave Peak in April

	Illness and Care of Sick	Psychological Demand	**Total**
% Level Impact			
January	-0.25	-0.05	**-0.30**
February	-1.98	-0.39	**-2.38**
March	-0.69	-0.14	**-0.82**
April	-0.30	-0.06	**-0.36**
May	-0.14	-0.03	**-0.16**
June - Dec	0.00	0.00	**0.00**
% Level Impact			
Q1	-0.97	-0.19	**-1.17**
Q2	-0.15	-0.03	**-0.18**
Q3	0.00	0.00	**0.00**
Q4	0.00	0.00	**0.00**
Year 1	**-0.28**	**-0.06**	**-0.34**
Year 2	0.00	0.00	**0.00**
p.p. Growth Impact			
Q1	-0.97	-0.19	**-1.17**
Q2	0.83	0.16	**0.99**
Q3	0.15	0.03	**0.18**
Q4	0.00	0.00	**0.00**

*quarterly rates

Table D.11: 1957 Scenario – Full Demand Reallocation; Low Absenteeism Impact on Output – Monthly and Quarterly GDP Impacts - Main Wave Peak in February, Second Wave Peak in April

	Illness and Care of Sick	Psychological Demand	**Total**
% Level Impact			
January	-0.08	-0.02	**-0.11**
February	-0.66	-0.17	**-0.83**
March	-0.23	0.13	**-0.10**
April	-0.10	0.04	**-0.06**
May	-0.05	0.02	**-0.03**
June	0.00	0.01	**0.01**
July - Dec	0.00	0.00	**0.00**
% Level Impact			
Q1	-0.32	-0.02	**-0.35**
Q2	-0.05	0.02	**-0.03**
Q3	0.00	0.00	**0.00**
Q4	0.00	0.00	**0.00**
Year 1	**-0.09**	**0.00**	**-0.09**
Year 2	0.00	0.00	**0.00**
p.p. Growth Impact			
Q1	-0.32	-0.02	**-0.35**
Q2	0.28	0.05	**0.32**
Q3	0.05	-0.02	**0.03**
Q4	0.00	0.00	**0.00**

*quarterly rates

Annex E – Low Social Density Occupations

Table E.1: Low Social Density Occupations – United States – 1910

Agriculture, Forestry and Animal Husbandry	12,659,203
Extraction of Minerals	964,824
Brick and Stonemasons	169,402
Blacksmiths	232,988
Builders and Building Contractors	174,422
Carpenters	817,120
Engineers	245,554
Labourers - Building Trades	934,909
Machinists and Millwrights	488,049
Mechanics	34,787
Oilers of Machinery	14,013
Shoemakers and Cobblers (not in factory)	69,570
Painters	337,355
Paper Hangers	25,577
Plasterers	47,682
Plumbers	148,304
Roofers and Slaters	14,078
Sawyers	43,276
Canalmen and Lock Keepers	5,304
Longshoremen	62,857
Locomotive Engineers	96,229
Locomotive Firemen	76,381
Motormen	59,005
Switchmen, Flagmen and Yardmen	85,147
Mail Carriers	80,768
Telegraph and Telephone Linemen	28,350
Draymen, Teamsters and Expressmen	408,469
Brakemen	92,572
Lighthouse Keepers	1,593
Authors	4,368
Civil and Mining Engineers and Surveyors	53,963
Total	**18,476,119**
Total Gainfully Employed	38,167,336
Per Cent	**48.4**

Table E.2: Low Social Density Occupations – United States – 2004 (30 Largest; Accounting for 91 Per Cent of Employees in Socially Dense Occupations[7])

53-0000	Transportation and material moving occupations	9,597,380
49-0000	Installation, maintenance, and repair occupations	5,246,720
37-0000	Building and grounds cleaning and maintenance occupations	4,323,430
37-2011	Janitors and cleaners, except maids and housekeeping cleaners	2,119,800
53-3032	Truck drivers, heavy and tractor-trailer	1,594,980
53-3033	Truck drivers, light or delivery services	929,530
47-2031	Carpenters	913,130
47-2061	Construction laborers	892,940
37-3011	Landscaping and groundskeeping workers	866,950
53-7051	Industrial truck and tractor operators	626,910
47-2111	Electricians	621,050
47-1011	First-line supervisors/managers of construction trades and extraction workers	549,130
49-1011	First-line supervisors/managers of mechanics, installers, and repairers	455,560
45-0000	Farming, fishing, and forestry occupations	444,870
47-2152	Plumbers, pipefitters, and steamfitters	423,280
47-2073	Operating engineers and other construction equipment operators	369,280
43-5052	Postal service mail carriers	346,000
47-2141	Painters, construction and maintenance	248,900
45-2092	Farmworkers and laborers, crop, nursery, and greenhouse	231,120
49-2022	Telecommunications equipment installers and repairers, except line installers	198,450
47-2051	Cement masons and concrete finishers	195,020
47-2211	Sheet metal workers	181,720
49-9098	Helpers--installation, maintenance, and repair workers	160,020
49-9052	Telecommunications line installers and repairers	148,740
47-4051	Highway maintenance workers	139,740
53-7081	Refuse and recyclable material collectors	138,700
49-9099	Installation, maintenance, and repair workers, all other	129,840
47-2081	Drywall and ceiling tile installers	122,240
47-2181	Roofers	117,360
47-2021	Brickmasons and blockmasons	114,400

[7] The complete list is available from the authors on request.

Table E.3: Low Social Density Occupations – Canada – 2005 (thousands; 45 Largest; Accounting for 65 Per Cent of Employees in Socially Dense Occupations)

H711: Truck Drivers	223.0
H812: Material Handlers	189.7
G933: Janitors, Caretakers and Building Superintendent	181.6
G931: Light Duty Cleaners	145.0
B571: Shippers and Receivers	137.9
H421: Motor Vehicle Mechanic, Technical and Mechanical Repairer	112.1
H821: Construction Trades Helpers and Labourers	101.7
H326: Welders And Related Machine Operators	94.7
H121: Carpenters	92.7
H411: Const Millwright and Industrial Mechanic(Excluding Textile)	86.3
H611: Heavy Equipment Operators (Except Crane)	66.3
H211: Electricians (Excl Industrial and Power System)	62.8
H714: Delivery Drivers	56.7
I021: General Farm Workers	56.4
I212: Landscaping and Grounds Maintenance Labourers	55.2
J194: Metalworking Machine Operators	53.9
H311: Machinists and Machining and Tooling Inspectors	52.6
J196: Other Metal Products Machine Operators	48.1
H412: Heavy-Duty Equipment Mechanics	47.2
J212: Motor Vehicle Assemblers, Inspectors and Tester	40.1
F141: Graphic Designers and Illustrating Artists	39.9
J132: Plastics Processing Machine Operators	38.7
J314: Labourers In Wood, Pulp and Paper Processing	36.3
B575: Dispatchers and Radio Operators	33.6
A141: Facility Operation and Maintenance Managers	33.1
B562: Letter Carriers	30.2
H111: Plumbers	30.2
G932: Specialized Cleaners	29.9
C141: Electrical and Electronic Engineering Technology	28.4
B314: Property Administrators	25.7
J222: Furniture and Fixture Assemblers and Inspectors	25.5
H212: Industrial Electricians	25.3
J312: Labourers In Metal Fabrication	25.3
H422: Motor Vehicle Body Repairers	25.0
H016: Contractors and Supervisors, Mechanic Trades	24.5
H019: Contract and Supervisory, Other Construction Trades, Installer	24.5
A371: Construction Managers	24.2
I022: Nursery and Greenhouse Workers	24.1
H521: Printing Press Operators	24.0
H144: Painters and Decorators	23.2
B563: Couriers and Messengers	22.4
H531: Residential and Commercial Installer and Servicer	21.7
H83 Public Works and Other Labourers, N.E.C.	21.5
J213: Electronic Assembler, Fabricator, Inspector , Tester	21.0
H216: Telecommunications Installation and Repair Work	19.6

Glossary of Terms

Absenteeism Rate	The proportion of a relevant population that is absent from work at a given point in time.
Case Mortality Rate	The proportion of those who become clinically ill that dies of the illness.
Excess Absenteeism Rate	The proportion of a relevant population that is absent from work at a given point in time minus the percentage normally absent from work at a comparable point in time.
Excess Mortality Rate	The proportion of a relevant population that dies from a particular illness during some period, minus the percentage that would normally die from this illness during a comparable time period.
Gross Attack Rate	The proportion of a relevant population that becomes clinically ill (exhibits symptoms) during a pandemic wave or multiple waves. The gross attack rate is a cumulative concept.
Morbidity Rate	The proportion of a relevant population that is clinically ill (exhibits symptoms) at a given point in time.
New Case Incidence Rate	The proportion of the population that begins an illness spell on a given day.

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