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Exploring the Dependence between Mortality and Market Risks

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Abstract

In this paper, we develop a statistical approach to explore empirically the dependence between risks in the extremes. We apply it to study the dependence between mortality and market risks. With data for 6 developed countries, extending over 80 years, we pick the worst 10 years of mortality and compare their averages to the whole sample averages. We observe a reduction of the performance of some financial variables and an increase in correlation, but the effect remains weak and difficult to assess statistically. Moreover, our samples do not contain any significant pandemic outbreak, which limits our ability to explore very extreme events.

To complement this study, we put in the appendix ***an econometric study by Philippe Trainar*** *who examines the dynamic consequences of the Spanish Flu on the US market. He concludes that on a one year time horizon, he cannot detect a signi-ficant effect. This study shows how we could conduct a wider analysis if we had more data with higher frequency like monthly data.*

The Art & Science of Risk

1 Introduction

The current solvency regulations are emphasizing for the capital assessment of the tails of the distribution. Solvency II requires the estimation of the Value-at-Risk (VaR) at the 99.5% probability while the Swiss Solvency Test requires the estimation of the Tail-Value-at-Risk at the 99% probability. Both cannot be reasonably computed without a good understanding of catastrophic risks like earthquakes or pandemic. Modelling a portfolio does not only require the knowledge of each of the risks but also a good grasp on the degree of dependence between the various risks in extreme situations. It is well known that this dependence can be very important in case of catastrophic risks while quite weak in normal situation. This means that most of the data we have are not relevant in this case. We thus need to develop other methods to estimate this parameter.

One of the biggest risk facing a large reinsurer like SCOR is mortality. At the same time, the assets we would use to pay a series of big mortality claims are largely invested in financial markets. Imagine that a severe pandemic breaks out in the world, will this have ripple effects on the economy and/or on financial markets thus depreciating the assets the company holds to pay those claims? Undoubtedly, it is a very important question for risk management. Modelers are thus faced with the difficult problem of coming up with reasonable estimates for the possible dependence between mortality risk and market risks in case of stress. The goal of this paper is to provide some empirical evidence of a changing behavior of the economy and the financial markets during periods where the mortality is relatively high.

A search in the literature showed that most of the papers on the subject are prospective and contradictory since there is little experience. It is hard to find well founded results even though there is a lot of good work done on the link between population and economy, which is not exactly the same problem. Some historical studies have been done on the consequences of the big pest plague, but their relevance to our modern economy seems doubtful, notwithstanding the lack of reliable statistical data for this period. More interesting are the studies on the 1918 influenza as this event remains the benchmark of most of the current pandemic models. Most of the papers do not come up with strong conclusions in this sense. A paper by Brainerd and Siegler [3] points out to a strong economic recovery in the subsequent years, while a very good review article by Garrett [10] concludes at the short-term effects on the economy. There are, however, a few cases where epidemic eruptions have caused documented economic disruptions like the SARS [4, 6] or the H1N1 viruses [5]. The recent study of the World Bank based on these events, which we just mentioned [6] concludes that a severe pandemic would cause global GDP contraction by up to 4.8% in just one year. This is really a massive effect. Large macro-economic models to study this problem come up with very wide estimate for the influence on the economy of a severe pandemic, Jonung *et al.* [12] conclude for Europe to effects varying from 2 to 4% losses in the GDP for a major pandemic.

Our approach differs from those above as we want to empirically look for effects based on an analysis of time series data following a study by Ribeiro and di Pietro from JPMorgan [13] who concentrated on mortality "spikes", defined as the years with mortality changes above 1.5 times the standard deviation (positive and negative) for the US mortality index and looked at the performance of the stock market during these years using the Dow Jones Industrial Average (DJIA) in conjunction with US mortality data. They conclude at a severe drop of the average performance of the index when mortality spikes up (-4.9% versus an average performance of 4.9%) and above performance when mortality improves (13.2% versus 4.9%). Concentrating on the extremes and comparing the results to the sample average is a promising approach to explore possible changes in the behavior of the risks.

The paper is organized as follows, in a first section, we present the methodology used for the statistical analysis. Section 2 is devoted to explain our methodology, while, in Section 3, we present the data and their treatment for the study. We discuss the results in Section 4 and conclude in Section 5. Appendices A and B contain results varying the parameters. In the first, we present results varying the size of the extreme sample. In the second, we present results varying the definition of the mortality indices. In Appendix C, we present an econometric study conducted by our chief economist officer on the Spanish Flu with more frequent (monthly) data. His conclusion is that there is no significant effect over a one year horizon.

2 Methodology

Inspired by [13], we have adopted in this study a similar method. However, the results of Ribeiro and di Pietro are made with just one country and a particular variable, the DJIA. Moreover, their selection criterion for the mortality spikes is simply a multiple (1.5) of the standard deviation. In our case, we explore this effect using the 10 worst yearly change in mortality of the sample. This criterion is more robust as it does not assume the existence of the second moment of the underlying distribution. It is based on the empirical quantiles (see for instance [9] for a similar approach). To ensure the statistical quality of our results, we also vary the parameters, exploring various economic/financial variables, and choosing a larger number of countries than only the US. Another difference is that our stock index is the S&P 500, which is more representative of the US stock market since it contains a wider variety of companies than the Dow Jones Industrial Average.

Our starting point is a mortality index for a particular country. We build a yearly index based on the average life expectancy at birth for the whole population (male and female) [11] and look at its logarithmic change year-by-year (eq.(2)). The variable, life expectancy at birth, denoted e_0, is defined as the average number of years a newborn child would live. The life expectancy estimates used here are period estimates. This means that the life expectancy for each year is computed using the mortality information of the current year and not using the information of the birth cohort over the future years. This way ensures that we can use the results for the internal model. In this case, we do not have access to future information as we would have if we used historical studies.

We then choose the worst 10 years (excluding the First and Second World Wars 1914 to 1918 and 1939 to 1945, respectively), which we report in Table 1 together with the value of the changes in percent. For these years, we look at the performance of various economic and financial indicators

Table 1: The ten worst years of the changes in mortality index (and their values) by country.

US		UK		JP		FR		SW		AU	
Year	Rate	Year	Rate	Year	Rate	Year	Rate	Year	Rate	Year	Rate
1934	(-1.07%)	**1924**	(-2.10%)	**1956**	(-0.21%)	**1884**	(-1.82%)	**1905**	(-1.57%)	**1923**	(-1.85%)
1936	(-0.89%)	**1927**	(-1.03%)	**1957**	(-0.20%)	**1886**	(-1.84%)	**1908**	(-1.01%)	**1926**	(-0.48%)
1957	(-0.33%)	**1929**	(-3.90%)	**1980**	(-0.04%)	**1890**	(-4.89%)	**1910**	(-1.07%)	**1934**	(-0.98%)
1960	(-0.09%)	**1931**	(-1.27%)	**1988**	(-0.10%)	**1898**	(-4.14%)	**1914**	(-0.70%)	**1946**	(-0.67%)
1962	(-0.19%)	**1936**	(-0.32%)	**1990**	(0.01%)	**1899**	(-1.69%)	**1915**	(-1.85%)	**1951**	(-0.44%)
1963	(-0.24%)	**1949**	(-0.41%)	**1995**	(-0.19%)	**1906**	(-1.29%)	**1918**	(-16.68%)	**1959**	(-0.58%)
1966	(-0.04%)	**1951**	(-0.57%)	**1999**	(-0.04%)	**1911**	(-6.44%)	**1924**	(-1.58%)	**1962**	(-0.32%)
1968	(-0.43%)	**1961**	(-0.35%)	**2005**	(-0.13%)	**1925**	(-1.61%)	**1927**	(-1.96%)	**1964**	(-0.55%)
1980	(-0.12%)	**1968**	(-0.53%)	**2010**	(-0.07%)	**1929**	(-2.10%)	**1931**	(-0.83%)	**1968**	(-0.49%)
1993	(-0.26%)	**1972**	(-0.32%)	**2011**	(-0.28%)	**1949**	(-1.39%)	**1944**	(-1.44%)	**1970**	(-0.56%)

and compare them with the average performance over the whole sample. This gives us already an indication of changes of the behavior in the extremes. Concentrating on yearly results and on the extreme changes gives us a way to look at the effect beyond a simple short-term dynamics as it would be the case if we only looked at a particular pandemic eruption or a particular event. If there is any effect, it will be due to underlying causes that affect both risks at the same time. To ensure enough depth to our analysis, we extend the study to six countries and 4 different variables: GDP, CPI, stock index and 10y government yield. This is another important difference to [13].

To analyse the statistical significance of the results, we bootstrap with replacement[1] in the full sample 10'000 sets of 10 years of data from which we compute the average. We thus obtain an empirical distribution of those averages. Such a technique gives us the possibility to explore the variability of our result in the data. Out of those empirical distributions, it is possible to estimate the probability of the average in the extremes, also called p-values:

$$\text{p-value} = \boldsymbol{P}(X \leq x) = 1 - \boldsymbol{P}(X > x) \tag{1}$$

where x is the value we found for the extreme sample.

The values displayed in Table 1 are for the samples of mortality data. To do our analysis, we need also data from 4 other time series, Gross Domestic Product (GDP), inflation index (here we choose the Consumer Price Index, CPI), stock indices and the 10y yield of government bonds. In our case, data availability is not the same for every time series. We thus have to choose the largest common set for each country. In the tables presenting the results we report the exact sample for each of the countries (excluding the two World Wars, except for Sweden). In Table 1, we see that the largest

[1] Bootstrap with replacement means that we randomly choose a set of n data, where n is the size of the extreme sample out of the N data of the whole sample. We do this at every step, which means we always pick n out of N.

Table 2: List of the main pandemic, the year when it started, and the number of deaths attributed to them during the last century (in million)

Year	1918	1957	1968	1981	2002	2006	2014
Type	Spanish Flu	H2N2 Asian Flu	H3N2 HK Flu	AIDS	SARS	H5N1 Avian Flu	Ebola Virus
Deaths	30	4	2	25	0.008	0.002	0.006

change happens in 1918 in Sweden. This country being neutral did not participate in the first world war but was submitted to the pandemic as the others and was subject to the Spanish Flu. It is why we see a change of more than 16% in 1918. It is the only double digits change we experience in the whole set. We also see that there are not many worst years that are similar for all the countries, but there are years like 1968 that are in the worst samples for few countries like US, UK and AU. This year corresponds to the outbreak of the Hong Kong Flu.

To complement Table 1, we also present in Table 2, the main pandemic episodes during the same period and as a benchmark the Spanish Flu of 1918, which remains the latest big pandemic. We see that there has not been as severe a crisis as the one of 1918, except for AIDS but which did not happen overnight. The 25 million deaths are accounted for on a period of more than 10 years. In fact, the number of deaths is aggregated on a long period. The latest surge of viruses have been more benign, although we do not know up to today what is going to be the final death-toll of the current Ebola pandemic. It is already now deadlier than the Avian flu of 2006. The latest numbers released by the WHO were 6'331 dead by December 8, 2014 after nine months of the Ebola virus spreading out into 42 countries as of today.

We see, by comparing the years of Table 1 to those of Table 2 that the worst years do not really correspond to an outburst of a pandemic (except 1968 and the Hong Kong Flu for US, UK and AU), but are rather linked to problems in the societies of those countries. This reduces the dependence that we are going to find with financial and economic data, when looking at the data on the same year. To explore the dynamics of the results, we use the lead-lag correlation analysis, according to the methodology developed in Dacorogna *et al.* [7]. We lead and lag the economic variables in relation to the mortality indices during those extreme years to see if there are retarded effects. We compute the correlation over 5 years lag and 5 years lead. This analysis allows us to see if any of the economic or financial indicators have an effect on the mortality indices (lag-analysis), or if the mortality indices have lagged effects on the economic or financial indices (lead-analysis).

3 Description of the data

For the mortality data, we use the Human Mortality Database publicly available on `http://www.mortality.org`. This site provides comprehensive yearly data on the subject. We have chosen six representative countries for our study: United States (US), United Kingdom (UK), Japan (JP), France (FR), Sweden (SW) and Australia (AU), where the life insurance industry is well established as well as financial markets are sufficiently developed to reflect all information available at any point in time. The mortality data are quite granular, but we are going to use an index representing the whole population.

For economic and financial data we use mainly data collected by Global Finance Data `http://www.globalfinancedata.com`, but, in order to obtain long enough time series for the French GDP, we use for it the data from Barro and Ursùa (2008) [1]. The choice of essentially a unique source of financial and economic data is to ensure consistency among various countries. We end up with long time series that are mostly limited by the availability of mortality data in particular for Japan and for the US: US starts in 1933 and JP in 1946. FR is the country that ends up to have the longest sample, from 1880 to 2009. The stock indices chosen are the S&P 500 for the US, the FTSE All-Share Index for the UK, the Tokyo SE Price Index (TOPIX) for Japan, the CAC All-Tradable Index for France, OMX Affärsvärldens General Index for Sweden, and the All Ordinaries Index for Australia.

The GDP and the stock indices are then treated in terms of logarithmic changes:

$$x_i = \ln(p_i) - \ln(p_{i-1}) \tag{2}$$

where x_i represents one of the indices used in the analysis. The logarithmic return constitutes the basic variable we analyze here. In all our statistics, unless stated otherwise, we use this variable. For the Government Yield and the CPI we simply use an average of the yields and the inflation.

The frequency of the data is yearly since it is the relevant time horizon for computing the mortality indices and the major macro-economic data. Of course, data at higher frequency, like quarterly or monthly, would be required to analyze the dynamics of the market response to a pandemic eruption, but our purpose here is to see if there is a sort of "long-term" dependence that could affect an insurance company in terms of its solvency. Our data sample is not uniform over the various countries. Japan for instance, starts only after the second world war and the US only in 1933. We also eliminate from our sample the years of the First and Second World Wars (1914-1918 and 1939-1945) for all countries directly involved in it (except Sweden, which stayed neutral both times) as they would introduce a bias due to the war conditions. This, of course, excludes the year 1918, which was the year of the outburst of the Spanish Flu. We will discuss this in the next section.

Table 3: We report the *average performance* of various economic indicators compared to the sample average. The sample size for the extremes is 10 worst years. For stock indices and 10y government yields, we also report the *reduction* of the average performance compared to the sample average. In parenthesis, we present the p-values computed using eq.(1) for the averages of the extreme sample.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	4.48% (93%)	3.17% (91%)	3.91% (27%)	2.81% (67%)	0.53% (4%)	4.24% (87%)
full sample	3.19%	2.26%	4.98%	2.47%	2.87%	3.47%
extreme + 1 year	4.25% (89%)	2.15% (46%)	3.19% (14%)	2.59% (71%)	6.60% (100%)	4.47% (93%)
Inflation						
extreme	3.26% (47%)	2.72% (26%)	1.39% (7%)	2.25% (24%)	5.21% (81%)	4.73% (71%)
full sample	3.64%	3.86%	3.89%	4.58%	3.64%	4.21%
Stock						
extreme	2.78% (25%)	2.86% (36%)	5.95% (40%)	−0.40% (19%)	1.53% (27%)	7.47% (62%)
full sample	6.50%	5.16%	8.47%	5.02%	5.79%	5.93%
reduction	*57.3%*	*44.7%*	*29.8%*	*108.1%*	*73.6%*	*-26.0%*
10Y Gov. Yield						
extreme	4.96% (40%)	5.31% (20%)	4.79% (27%)	3.75% (3%)	4.25% (10%)	4.78% (6%)
full sample	5.54%	6.55%	5.75%	5.57%	5.64%	6.72%
reduction	*10.4%*	*18.9%*	*16.7%*	*32.6%*	*24.6%*	*28.8%*

4 Discussion of the results

In Table 3, we present the results for the averages computed on the samples of extremes (10 worst years for the change of the mortality index) and the averages computed on the whole sample. We note in these results that the averages are worse for the financial returns in all cases (except for stocks in AU) while the macro-economic values show better results; higher GDP growth (except for JP and SW) and lower inflation (except for SW and AU). We should not forget here that the worst years do not correspond to a strong pandemic (except for SW, with the Spanish Flu, which shows in both case a worsening of the macro-economic data), but rather to a worsening of the life expectancy improvements. In this case, we can assume that there is a lag in the effect of mortality on the macro-economic data while they seem to have a direct effect on financial markets both on stocks and government yields. To explore this hypothesis, we do the same statistics looking at the GDP one year after the bad year on the mortality index. We see in Table 3 that the GDP is worse than the average in the UK and JP cases after the bad period of mortality. We also observe a worsening of the average for the US and FR. It is a sign that the effect on macro-economic variables is not important when there is no serious pandemic outbreak but could take longer to manifest itself when the fall in life expectancy is due to social and/or other causes than purely the spread out of a deadly disease.

For the stock indices and the 10y government yields, we also show in Table 3, the reduction, R, in mean from the extremes, $\bar{x}_e$, to the mean, $\bar{x}_s$, over the whole sample:

$$R = \frac{\bar{x}_e - \bar{x}_s}{\bar{x}_s} \tag{3}$$

A negative reduction would mean that there is no reduction but an increase in comparison with the sample mean. We show a reduction of around 60% for the stocks and 20% for the government yields. The statistical significance of those results is limited if looked at on each time series alone (except for the government yield in FR), but the fact that it is experienced across all countries and for both financial indicators is a sign that some effect exists. Our results for the US differ sensibly to those of [13]. We explain the difference by the fact that we use a shorter sample but better mortality data and a different stock index than Ribiero and di Pietro. Nevertheless, our results go in the same direction: a large reduction of the stock index performance during mortality spikes. Overall, this analysis provides only evidence of a weak effect. We see further evidences of this effect when studying lead/lag correlations where correlation increases when the mortality index is lagged. Furthermore, in the appendix, we show similar results with different mortality indices. They confirm the results presented in Table 3.

To complement the performance study of our economic and financial variables, we also explore the correlation between our variables. In Table 4, we present the results for the correlation within the sample and within the extremes. First of all let us notice that there is no strong correlation between our chosen variables and the mortality in the full sample, except for the CPI in Japan (a correlation of 0.71) but this could well be spurious due to the relative short sample we have and the fact that we do not observe similar behaviors in the other countries. However, we see here that, except for JP, correlation is stronger in the extreme sample than on the average sample. The statistical significance, illustrated by the p-values, is stronger than in Table 3. We find that some correlation appears on the financial variables in the extreme samples where there was no correlation on the whole samples. It is worth noting that if we reduce the number of worst years to 5, the difference generally increases, with a lower significance however due to the lower number of observations in the sample. For instance, the correlation in the extreme for US stock goes from -0.18 to -0.22 and for government yield from 0.42 to 0.68. We also explored the case where we increase the number of worst years to 15 and 20. In this case, the differences diminishes with increasing n. However, we do not see a stability in the numbers there, indicating that the effect exists but its extent is impossible to assess with the data we have. Moreover, in these cases, the p-values are all relatively small and do not allow to conclude.

The case of Sweden is peculiar. We see a strong negative correlation in the extremes both for CPI (-0.93) and for the 10y government yield (-0.60). Both values are highly significant with p-values of 4% and 1% respectively. In Table 3, we do not observe a different behavior of this country compared to the others. For instance, we see a decrease of the 10y yield as for others, which is contrary to what we would expect with a negative correlation. The situation is slightly different for CPI, where we see an increase of inflation in the extreme sample as a strong negative correlation would seem to indicate. Those differences might be due to the fact that, contrary to the other country, we include in the Swedish sample the year 1918 which is marked by the surge of the Spanish Flu.

Table 4: We report the *correlation* of various economic indicators with the mortality index within the extreme sample (correx) compared to the sample average. The sample size for the extremes is 10 worst years. For the correx, we put in parenthesis the p-values computed using eq.(1).

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	−0.84 (3%)	0.07 (71%)	0.12 (11%)	−0.58 (10%)	0.24 (51%)	0.12 (78%)
full sample	−0.40	−0.15	0.41	0.30	0.35	−0.14
Inflation						
extreme	0.31 (57%)	0.46 (93%)	0.35 (58%)	0.01 (49%)	−0.93 (4%)	0.16 (67%)
full sample	0.10	−0.17	0.71	0.29	−0.42	−0.16
Stock						
extreme	−0.18 (26%)	0.26 (83%)	−0.00 (21%)	−0.45 (6%)	0.27 (83%)	−0.15 (25%)
full sample	0.05	−0.06	0.40	0.07	−0.03	0.01
10Y Gov. Yield						
extreme	0.42 (90%)	0.22 (87%)	0.04 (16%)	0.44 (98%)	−0.60 (1%)	−0.17 (12%)
full sample	−0.12	−0.12	0.11	−0.06	−0.04	0.09

The results of the lead-lag correlation are also inconclusive, but pointing to an increase of the correlation with GDP when mortality is lagged.

5 Conclusion

Through a novel empirical investigation, we analyze the relation between the mortality risk and the economic and financial risks. This study extending on different countries over more than 80 years show some direct weak effects on the financial markets and on the correlation, when the mortality index experiences its worst years. Unfortunately, those results do not allow us to definitely conclude on the calibration of a dependence between these risks. Nevertheless, it gives us a first idea that financial markets are affected by the severe worsening of mortality. A last example of this influence was given on September 30, 2014: when the first Ebola case was identified in the US, the equity market for American aviation companies went down 2.5%. From this example, however, it is difficult to conclude on a lasting effect. The absence of a serious pandemic spreading rapidly around the world, does not give us enough elements for finding direct effects on macro-economic variables, but we find some lagged effects that would probably be shorter in case of a serious outbreak of a pandemic.

The extent of the effect over 5 countries out of 6 for stock indices and for all the countries for government yield indicate that indeed mortality and market risks are correlated in the extremes. However, this effect remains weak and does not allow us to conclude definitely on the size of this dependence as our samples do not contain extreme downturns in the mortality indices. In our study, the mortality downwards movements affect mostly financial markets and not directly macro-economic data because in those years, we did not experience a severe pandemic across the world. We expect that, in this case, we could see effects on macro-economic indicators.

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A Varying the sample size for the extremes

Analyzing the stability of the results is difficult with the type of analysis done in this study. In these appendices, we show various ways to look at the problem. The first one is by varying the sample size of the extremes. Instead of simply using a size of 10, we vary it from 5 to 20. We see, in Table 5, that the results remain essentially the same independently of n but weaken of course when n becomes large. We can thus conclude that our study that isolates the extreme does not materially depend on the size of the sample as long as it is not too big in proportion of the whole sample.

Table 5: We report the *average performance* and the *reduction* in comparison with the full sample performance of the stock indices and the 10Y Government Yield in the extreme sample as a function of the sample size, n, varying it from 5 to 20 worst years.

Variable	n=5	n=10	n=15	n=20
US:				
Stock	3.43% (33%)	2.78% (25%)	6.15% (52%)	2.84% (19%)
reduction	*47.29%*	*57.31%*	*5.37%*	*56.36%*
10y Gov. Yield	4.14% (17%)	4.96% (40%)	5.55% (77%)	5.16% (69%)
reduction	*25.18%*	*10.39%*	*-0.24%*	*6.88%*
UK:				
Stock	−3.00% (16%)	2.86% (36%)	5.40% (56%)	3.62% (39%)
reduction	*158.12%*	*44.68%*	*-4.51%*	*29.90%*
10y Gov. Yield	4.44% (8%)	5.31% (20%)	5.96% (48%)	6.23% (71%)
reduction	*32.22%*	*18.86%*	*8.88%*	*4.87%*
JP:				
Stock	5.37% (40%)	5.95% (40%)	5.48% (36%)	−1.07% (3%)
reduction	*36.61%*	*29.76%*	*35.34%*	*112.62%*
10y Gov. Yield	4.95% (33%)	4.79% (27%)	4.78% (32%)	4.60% (30%)
reduction	*13.92%*	*16.65%*	*16.89%*	*19.96%*
FR:				
Stock	2.78% (40%)	−0.40% (19%)	−0.39% (14%)	6.10% (64%)
reduction	*44.66%*	*108.06%*	*107.84%*	*-21.52%*
10y Gov. Yield	3.31% (2%)	3.75% (3%)	3.69% (1%)	4.01% (3%)
reduction	*40.64%*	*32.65%*	*33.82%*	*28.12%*
SW:				
Stock	17.59% (90%)	1.53% (27%)	3.66% (36%)	7.32% (69%)
reduction	*-203.8%*	*73.62%*	*36.77%*	*-26.45%*
10y Gov. Yield	4.63% (28%)	4.25% (10%)	4.17% (6%)	5.01% (42%)
reduction	*17.90%*	*24.64%*	*26.09%*	*11.15%*
AU:				
Stock	9.02% (64%)	7.47% (62%)	3.71% (33%)	4.61% (42%)
reduction	*-52.01%*	*-25.96%*	*37.50%*	*22.25%*
10y Gov. Yield	4.81% (10%)	4.78% (6%)	5.93% (40%)	6.46% (73%)
reduction	*28.36%*	*28.77%*	*11.74%*	*3.85%*

B Varying the mortality index

Another way to explore the stability of the results is to look for other way of qualifying the mortality of the population and to look at ages classes where people are mostly economically active. We thus redo the statistics presented above simply changing the mortality index definition.

We define the mortality rate $q_{t,r}$ for a range $r = 25-50$, as the ratio between the number of deaths $D_{t,r}$ occurring in a year t in a population of individuals aged between 25 and 50 at the beginning of that year by the number of individuals $P_{t,r}$ of these ages in the population, i.e. (see e.g. [11])

$$q_{t,r} = \frac{D_{t,r}}{P_{t,r}}. \tag{4}$$

Another variation of the mortality index to capture the mortality between age 25 to 50, is to use the mortality index between 25 and 50 weighted by the population size of each age. For a given year t, we compute the weighted mortality index as follows:

$$\tilde{q}(t,r) = \sum_{x=25}^{50} w_{t,x} q_{t,x}$$

where $w_{t,x} = P_{t,x} / \sum_{x=25}^{50} P_{t,x}$. Knowing that $q_{t,x} = D_{t,x}/P_{t,x}$, the expression for $\tilde{q}(t,r)$ can be expressed as

$$\tilde{q}(t,r) = \sum_{x=25}^{50} D_{t,x} / \sum_{x=25}^{50} P_{t,x} \tag{5}$$

This index is not very different than the one defined in eq. 4, thus it is not surprising that it will find the same worst years for certain countries: US, UK and JP (see Tables 6, 7, 8) while slighty different years (one or two) for the three other cases: FR, SW and AU (see Tables 9, 10, 11).

The mortality entropy $S_{t,r}$, for a range r, is defined by the entropy of the curve of deaths at age 25 for individuals aged between 25 and 50 at the beginning of the year t. This curve consists of the probabilities $p_{t,x}$ which represent the probability, at age 25, of dying in the xth year of life (see [8]).

The computation of $S_{t,r}$ is thus given by

$$S_{t,r} = \sum_{x=25}^{50} -p_{t,x} \times \log(p_{t,x}) \tag{6}$$

Following the usual notion of entropy, our mortality index $S_{t,r}$ would evaluate the concentration level of the curve of deaths. Hence, this index allows the analysis of the evolution of these curves through time.

Note that, in industrialized countries, the curves of deaths for the age between 25 to 50 are becoming over the years much more flat, which means an increase in $S_{t,r}$.

Inspired by the notion of variation coefficient (see e.g. [14], pp. 169-171), we define the mortality variation coefficient $VC_{t,r}$, for a range r, as the ratio of the standard deviation to the mean of the number of deaths in year t at ages x, $D_{t,x}$, being x = 25, ..., 50. Using $D_{t,x}$'s, we compute this mortality index as

$$VC_{t,r} = \frac{\sqrt{\frac{1}{25}\sum_{x=25}^{50}\left(D_{t,x}-\overline{D}_t\right)^2}}{\overline{D}_t} \tag{7}$$

where $\overline{D}_t = \dfrac{1}{26}\displaystyle\sum_{x=25}^{50} D_{t,x}$.

Given a population of size P_t at year t, these numbers of deaths can be computed using the curve of deaths by $D_{t,x} = p_{t,x} \times P_t$ for x = 25, ..., 50. This shows that VC_t is independent of P_t.

Similar to the usual variation coefficient, our mortality index $VC_{t,25-50}$ measures the variability of numbers $D_{t,x}$'s without considering the unit of measurement of these numbers and it can be used to compare curves of deaths obtained in different years.

In Table 6 and 10, we display, for the US and SW respectively, the various samples for the 10 worst years obtained for the various indices. They are quite different from one index to the other. For SW in particular, the year 1918 of the Spanish Flu disappears from the sample of worst years and is replaced by 1919. Moreover, the variation coefficient gives too much weight to the last years of the sample. It is therefore not astonishing that we see in Tables 16 and 17 a very different behavior than for the other indices. For the latter cases (Tables 12, 13, 14, 15), we see, most of the time, a similar behavior than in Tables 3 and 4 with some noticeable exceptions like the stock indices for JP and FR in Tables 12 and 14 for the mortality rate and entropy respectively for the age between 25-50.

Table 6: The ten worst years of the changes in mortality indices (and their values) for various indices, and for US.

Expected lifetime	Mortality rate	Entropy	Variation coefficient	Weighted rate
1934 (-1.07%)	**1937** (-3.92%)	**1937** (-3.23%)	**1964** (-2.11%)	**1937** (-4.23%)
1936 (-0.89%)	**1938** (-10.30%)	**1938** (-8.48%)	**1969** (-2.87%)	**1938** (-11.00%)
1957 (-0.33%)	**1946** (-5.97%)	**1946** (-5.03%)	**1979** (-3.17%)	**1946** (-6.27%)
1960 (-0.09%)	**1948** (-3.76%)	**1948** (-3.23%)	**1984** (-3.32%)	**1948** (-3.94%)
1962 (-0.19%)	**1954** (-5.74%)	**1954** (-4.77%)	**1986** (-7.79%)	**1954** (-5.91%)
1963 (-0.24%)	**1974** (-4.60%)	**1974** (-3.90%)	**1987** (-2.71%)	**1974** (-4.74%)
1966 (-0.04%)	**1975** (-4.03%)	**1975** (-3.28%)	**1988** (-3.09%)	**1975** (-4.11%)
1968 (-0.43%)	**1982** (-4.91%)	**1982** (-4.12%)	**1989** (-3.10%)	**1982** (-5.02%)
1980 (-0.12%)	**1996** (-6.96%)	**1996** (-5.99%)	**2001** (-2.28%)	**1996** (-7.15%)
1993 (-0.26%)	**1997** (-6.61%)	**1997** (-5.76%)	**2006** (-2.50%)	**1997** (-6.78%)

Table 7: The ten worst years of the changes in mortality indices (and their values) for various indices, and for UK.

Expected lifetime	Mortality rate	Entropy	Variation coefficient	Weighted index
1924 (-2.10%)	**1923** (-8.77%)	**1923** (-7.19%)	**1930** (-4.15%)	**1923** (-9.39%)
1927 (-1.03%)	**1928** (-5.94%)	**1928** (-4.77%)	**1978** (-3.99%)	**1928** (-6.24%)
1929 (-3.90%)	**1930** (-11.73%)	**1930** (-9.39%)	**1987** (-3.51%)	**1930** (-12.31%)
1931 (-1.27%)	**1934** (-8.09%)	**1934** (-6.59%)	**1990** (-3.88%)	**1934** (-8.51%)
1936 (-0.32%)	**1938** (-9.16%)	**1938** (-7.47%)	**1994** (-5.23%)	**1938** (-9.56%)
1949 (-0.41%)	**1946** (-5.27%)	**1946** (-4.68%)	**1996** (-3.71%)	**1946** (-5.61%)
1951 (-0.57%)	**1948** (-8.73%)	**1948** (-7.27%)	**1998** (-3.39%)	**1948** (-9.03%)
1961 (-0.35%)	**1950** (-4.23%)	**1950** (-3.76%)	**2006** (-5.40%)	**1950** (-4.41%)
1968 (-0.53%)	**1952** (-9.80%)	**1952** (-8.30%)	**2007** (-3.34%)	**1952** (-10.08%)
1972 (-0.32%)	**1980** (-4.87%)	**1980** (-4.07%)	**2009** (-3.00%)	**1980** (-4.94%)

Table 8: The ten worst years of the changes in mortality indices (and their values) for various indices, and for JP.

Expected lifetime	Mortality rate	Entropy	Variation coefficient	Weighted index
1956 (-0.21%)	**1948** (-11.09%)	**1948** (-8.84%)	**1966** (-3.03%)	**1948** (-12.19%)
1957 (-0.20%)	**1949** (-7.92%)	**1949** (-6.37%)	**1983** (-2.39%)	**1949** (-8.73%)
1980 (-0.04%)	**1950** (-9.25%)	**1950** (-7.57%)	**1987** (-2.87%)	**1950** (-10.26%)
1988 (-0.10%)	**1951** (-14.02%)	**1951** (-11.57%)	**1994** (-2.06%)	**1951** (-15.25%)
1990 (0.01%)	**1952** (-12.76%)	**1952** (-10.59%)	**1995** (-2.02%)	**1952** (-13.65%)
1995 (-0.19%)	**1953** (-6.73%)	**1953** (-5.66%)	**1998** (-3.76%)	**1953** (-7.15%)
1999 (-0.04%)	**1955** (-7.82%)	**1955** (-6.58%)	**1999** (-1.61%)	**1955** (-8.25%)
2005 (-0.13%)	**1958** (-9.00%)	**1958** (-7.45%)	**2003** (-2.78%)	**1958** (-9.34%)
2010 (-0.07%)	**1971** (-6.11%)	**1971** (-5.09%)	**2009** (-1.56%)	**1971** (-6.24%)
2011 (-0.28%)	**2012** (-11.02%)	**2012** (-9.58%)	**2011** (-3.60%)	**2012** (-11.13%)

Table 9: The ten worst years of the changes in mortality indices (and their values) for various indices, and for FR.

Expected lifetime	Mortality rate	Entropy	Variation coefficient	Weighted index
1884 (-1.82%)	**1901** (-6.37%)	**1901** (-5.02%)	**1881** (-9.60%)	**1897** (-6.10%)
1886 (-1.84%)	**1908** (-6.08%)	**1908** (-4.79%)	**1884** (-7.22%)	**1901** (-7.12%)
1890 (-4.89%)	**1919** (-64.98%)	**1919** (-47.21%)	**1886** (-5.77%)	**1908** (-6.74%)
1898 (-4.14%)	**1920** (-27.16%)	**1920** (-21.57%)	**1893** (-9.19%)	**1919** (-86.55%)
1899 (-1.69%)	**1927** (-6.85%)	**1927** (-5.44%)	**1902** (-4.94%)	**1920** (-31.52%)
1906 (-1.29%)	**1946** (-51.37%)	**1946** (-41.86%)	**1911** (-7.76%)	**1927** (-7.37%)
1911 (-6.44%)	**1952** (-9.38%)	**1952** (-8.03%)	**1919** (-165.9%)	**1946** (-56.34%)
1925 (-1.61%)	**1958** (-10.48%)	**1958** (-8.62%)	**1961** (-5.90%)	**1952** (-9.79%)
1929 (-2.10%)	**1997** (-5.68%)	**1997** (-5.16%)	**1990** (-4.56%)	**1958** (-10.75%)
1949 (-1.39%)	**2004** (-6.07%)	**2004** (-5.17%)	**1991** (-6.06%)	**2004** (-6.16%)

Table 10: The ten worst years of the changes in mortality indices (and their values) for various indices, and for SW.

Expected lifetime	Mortality rate	Entropy	Variation coefficient	Weighted index
1905 (-1.57%)	**1916** (-7.29%)	**1916** (-5.85%)	**1903** (-8.66%)	**1916** (-7.79%)
1908 (-1.01%)	**1919** (-47.66%)	**1919** (-36.71%)	**1905** (-9.47%)	**1919** (-56.25%)
1910 (-1.07%)	**1920** (-13.49%)	**1920** (-10.89%)	**1911** (-8.43%)	**1920** (-15.09%)
1914 (-0.70%)	**1921** (-12.06%)	**1921** (-9.79%)	**1914** (-14.59%)	**1921** (-13.07%)
1915 (-1.85%)	**1923** (-11.45%)	**1923** (-9.35%)	**1919** (-143.7%)	**1923** (-12.24%)
1918 (-16.68%)	**1928** (-6.78%)	**1946** (-8.96%)	**1924** (-19.82%)	**1928** (-7.22%)
1924 (-1.58%)	**1946** (-10.36%)	**1948** (-9.55%)	**1943** (-11.70%)	**1932** (-7.04%)
1927 (-1.96%)	**1948** (-10.98%)	**1981** (-6.97%)	**1967** (-9.91%)	**1946** (-10.87%)
1931 (-0.83%)	**1981** (-7.94%)	**1995** (-5.59%)	**1982** (-8.20%)	**1948** (-11.43%)
1944 (-1.44%)	**2002** (-6.94%)	**2002** (-5.59%)	**2005** (-9.62%)	**1981** (-8.10%)

Table 11: The ten worst years of the changes in mortality indices (and their values) for various indices, and for AU.

Expected lifetime	Mortality rate	Entropy	Variation coefficient	New index
1923 (-1.85%)	**1922** (-7.93%)	**1922** (-6.66%)	**1923** (-5.00%)	**1922** (-8.53%)
1926 (-0.48%)	**1930** (-13.03%)	**1930** (-10.56%)	**1925** (-6.02%)	**1924** (-4.78%)
1934 (-0.98%)	**1932** (-5.43%)	**1932** (-4.62%)	**1928** (-4.33%)	**1930** (-13.63%)
1946 (-0.67%)	**1953** (-6.21%)	**1953** (-5.49%)	**1959** (-4.62%)	**1932** (-5.78%)
1951 (-0.44%)	**1971** (-6.65%)	**1971** (-5.62%)	**1968** (-6.32%)	**1953** (-6.44%)
1959 (-0.58%)	**1978** (-4.57%)	**1979** (-3.76%)	**1982** (-5.05%)	**1971** (-6.80%)
1962 (-0.32%)	**1981** (-4.56%)	**1981** (-3.75%)	**1985** (-4.59%)	**1978** (-4.62%)
1964 (-0.55%)	**1983** (-6.88%)	**1983** (-5.67%)	**1988** (-10.03%)	**1983** (-6.97%)
1968 (-0.49%)	**2001** (-6.79%)	**2001** (-6.03%)	**1995** (-8.05%)	**2001** (-6.93%)
1970 (-0.56%)	**2010** (-5.71%)	**2010** (-5.03%)	**1998** (-17.15%)	**2010** (-5.79%)

Table 12: We report the *average performance* of various economic indicators compared to the sample average. The sample size for the extremes is 10 worst years. The *mortality index* used here is the mortality rate defined in eq.(4) for ages between 25 to 50. In parenthesis, we present the p-values computed using eq.(1) for the averages of the extreme sample.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	0.41% (1%)	1.18% (11%)	7.16% (98%)	4.50% (93%)	4.74% (94%)	2.32% (13%)
full sample	3.19%	2.26%	4.98%	2.47%	2.87%	3.47%
extreme + 1 year	3.18% (53%)	1.79% (29%)	7.65% (99%)	2.18% (58%)	1.54% (15%)	2.27% (15%)
Inflation						
extreme	4.59% (88%)	1.57% (5%)	7.96% (95%)	11.43% (98%)	−0.26% (3%)	3.09% (26%)
full sample	3.64%	3.86%	3.89%	4.58%	3.64%	4.21%
Stock						
extreme	4.90% (39%)	1.82% (30%)	33.11% (100%)	11.61% (87%)	−2.66% (11%)	4.27% (39%)
full sample	6.50%	5.16%	8.47%	5.02%	5.79%	5.93%
reduction	*24.6%*	*64.7%*	*-291%*	*-131%*	*146.0%*	*27.9%*
10Y Gov. Yield						
extreme	4.93% (39%)	4.42% (4%)	6.28% (81%)	4.44% (16%)	5.52% (55%)	7.65% (89%)
full sample	5.54%	6.55%	5.75%	5.57%	5.64%	6.72%
reduction	*10.9%*	*32.4%*	*-9.1%*	*20.3%*	*2.2%*	*-13.9%*

Table 13: We report the *correlation* of various economic indicators with the mortality index within the extreme sample (correx) compared to the sample average. The sample size for the extremes is 10 worst years. For the correx, we put in parenthesis the p-values computed using eq.(1).The *mortality index* used here is the mortality rate defined in eq.(4) for ages between 25 to 50.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	0.29 (54%)	−0.14 (20%)	−0.66 (31%)	−0.77 (8%)	−0.80 (6%)	0.18 (60%)
full sample	0.34	0.19	−0.47	−0.37	−0.31	0.11
Inflation						
extreme	0.39 (90%)	0.52 (90%)	−0.22 (62%)	−0.72 (16%)	0.21 (57%)	0.72 (98%)
full sample	−0.12	0.05	−0.35	−0.45	0.41	0.05
Stock						
extreme	−0.43 (22%)	0.86 (100%)	−0.57 (33%)	−0.41 (14%)	0.35 (73%)	0.50 (90%)
full sample	−0.10	−0.06	−0.43	−0.15	0.01	0.07
10Y Gov. Yield						
extreme	0.22 (74%)	0.28 (78%)	0.55 (100%)	−0.04 (49%)	0.04 (50%)	0.24 (97%)
full sample	0.10	0.13	−0.26	0.04	0.03	−0.19

Table 14: We report the *average performance* of various economic indicators compared to the sample average. The sample size for the extremes is 10 worst years.The *mortality index* used for this table is the entropy defined in eq.(6) for ages between 25 to 50. In parenthesis, we present the p-values computed using eq.(1) for the averages of the extreme sample.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	0.41% (1%)	1.18% (11%)	7.16% (98%)	4.50% (93%)	4.99% (96%)	2.50% (17%)
full sample	3.19%	2.26%	4.98%	2.47%	2.87%	3.47%
extreme + 1 year	3.18% (53%)	1.79% (29%)	7.65% (99%)	2.18% (58%)	0.84% (6%)	2.15% (12%)
Inflation						
extreme	4.59% (88%)	1.57% (5%)	7.96% (95%)	11.43% (98%)	−0.04% (4%)	3.31% (32%)
full sample	3.64%	3.86%	3.89%	4.58%	3.64%	4.21%
Stock						
extreme	4.90% (39%)	1.82% (30%)	33.11% (100%)	11.61% (87%)	−3.88% (8%)	6.11% (52%)
full sample	6.50%	5.16%	8.47%	5.02%	5.79%	5.93%
reduction	*24.6%*	*64.7%*	*-291%*	*-131%*	*167.1%*	*-3.0%*
10Y Gov. Yield						
extreme	4.93% (39%)	4.42% (4%)	6.28% (81%)	4.44% (16%)	5.90% (71%)	7.78% (91%)
full sample	5.54%	6.55%	5.75%	5.57%	5.64%	6.72%
reduction	*10.9%*	*32.4%*	*-9.1%*	*20.3%*	*-4.6%*	*-15.8%*

Table 15: We report the *correlation* of various economic indicators with the mortality index within the extreme sample (correx) compared to the sample average. The sample size for the extremes is 10 worst years. For the correx, we put in parenthesis the p-values computed using eq.(1). The *mortality index* used for this table is the entropy defined in eq.(6) for ages between 25 to 50.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	0.27 (53%)	−0.13 (21%)	−0.62 (39%)	−0.82 (8%)	−0.79 (7%)	0.29 (71%)
full sample	0.34	0.20	−0.47	−0.39	−0.30	0.11
Inflation						
extreme	0.38 (89%)	0.49 (89%)	−0.16 (69%)	−0.76 (14%)	0.22 (58%)	0.75 (99%)
full sample	−0.11	0.05	−0.34	−0.47	0.40	0.06
Stock						
extreme	−0.44 (21%)	0.85 (100%)	−0.53 (36%)	−0.44 (13%)	0.33 (71%)	0.54 (92%)
full sample	−0.10	−0.06	−0.42	−0.16	0.01	0.06
10Y Gov. Yield						
extreme	0.21 (71%)	0.31 (79%)	0.58 (100%)	−0.02 (51%)	0.12 (63%)	0.34 (98%)
full sample	0.11	0.14	−0.26	0.04	0.03	−0.17

Table 16: We report the *average performance* of various economic indicators compared to the sample average. The sample size for the extremes is 10 worst years. For stock indices and 10y government yields, we also report the *reduction* of the average performance compared to the sample average. The *mortality index* is here the coefficient of variation defined in eq.(7) for ages between 25 to 50. In parenthesis, we present the p-values computed using eq.(1) for the averages of the extreme sample.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	3.02% (49%)	2.01% (42%)	1.47% (0%)	2.10% (45%)	5.25% (97%)	3.99% (79%)
full sample	3.19%	2.26%	4.98%	2.47%	2.87%	3.47%
extreme + 1 year	2.75% (34%)	1.67% (24%)	3.66% (25%)	3.49% (90%)	4.94% (95%)	2.62% (24%)
Inflation						
extreme	4.17% (79%)	2.45% (19%)	0.43% (0%)	3.06% (36%)	1.92% (20%)	4.21% (57%)
full sample	3.64%	3.86%	3.89%	4.58%	3.64%	4.21%
Stock						
extreme	6.34% (50%)	1.76% (30%)	8.97% (56%)	1.31% (28%)	10.65% (78%)	13.35% (93%)
full sample	6.50%	5.16%	8.47%	5.02%	5.79%	5.93%
reduction	*2.5%*	*65.8%*	*-5.9%*	*73.9%*	*-84.0%*	*-125%*
10Y Gov. Yield						
extreme	7.69% (100%)	7.03% (80%)	3.43% (2%)	4.90% (33%)	5.14% (40%)	8.14% (95%)
full sample	5.54%	6.55%	5.75%	5.57%	5.64%	6.72%
reduction	*-38.9%*	*-7.4%*	*40.3%*	*12.1%*	*8.9%*	*-21.2%*

Table 17: We report the *correlation* of various economic indicators with the mortality index within the extreme sample (correx) compared to the sample average. The sample size for the extremes is 10 worst years. For the correx, we put in parenthesis the p-values computed using eq.(1). The *mortality index* is here the coefficient of variation defined in eq.(7) for ages between 25 to 50.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	-0.01 (65%)	-0.35 (16%)	-0.22 (3%)	-0.51 (12%)	-0.81 (9%)	-0.13 (46%)
full sample	-0.23	-0.06	0.43	0.02	-0.40	-0.09
Inflation						
extreme	0.16 (74%)	0.07 (72%)	-0.43 (1%)	-0.93 (0%)	0.67 (91%)	0.11 (83%)
full sample	-0.06	-0.10	0.22	0.04	0.17	-0.17
Stock						
extreme	-0.26 (28%)	0.32 (90%)	0.63 (83%)	-0.32 (18%)	0.50 (93%)	0.13 (71%)
full sample	-0.06	-0.03	0.28	-0.02	-0.06	0.00
10Y Gov. Yield						
extreme	-0.16 (82%)	-0.07 (85%)	-0.00 (9%)	-0.00 (72%)	-0.02 (50%)	0.13 (92%)
full sample	-0.42	-0.37	0.18	-0.07	-0.02	-0.23

Table 18: We report the *average performance* of various economic indicators compared to the sample average. The sample size for the extremes is 10 worst years. For stock indices and 10y government yields, we also report the *reduction* of the average performance compared to the sample average. The *mortality index* is here the weighted mortality rate defined in eq.(5) for ages between 25 to 50. In parenthesis, we present the p-values computed using eq.(1) for the averages of the extreme sample.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	0.41% (1%)	1.18% (11%)	7.16% (98%)	4.01% (88%)	4.24% (88%)	2.28% (12%)
full sample	3.19%	2.26%	4.98%	2.47%	2.87%	3.47%
extreme + 1 year	3.18% (53%)	1.79% (29%)	7.65% (99%)	2.44% (66%)	1.24% (10%)	2.91% (35%)
Inflation						
extreme	4.59% (88%)	1.57% (5%)	7.96% (95%)	11.10% (98%)	−0.66% (2%)	1.74% (5%)
full sample	3.64%	3.86%	3.89%	4.58%	3.64%	4.21%
Stock						
extreme	4.90% (39%)	1.82% (30%)	33.11% (100%)	10.34% (82%)	0.00% (20%)	6.93% (58%)
full sample	6.50%	5.16%	8.47%	5.02%	5.79%	5.93%
reduction	*24.6%*	*64.7%*	*-291%*	*-106%*	*100.0%*	*-16.8%*
10Y Gov. Yield						
extreme	4.93% (39%)	4.42% (4%)	6.28% (81%)	4.20% (9%)	5.45% (53%)	6.75% (65%)
full sample	5.54%	6.55%	5.75%	5.57%	5.64%	6.72%
reduction	*10.9%*	*32.4%*	*-9.1%*	*24.7%*	*3.4%*	*-0.4%*

Table 19: We report the *correlation* of various economic indicators with the mortality index within the extreme sample (correx) compared to the sample average. The sample size for the extremes is 10 worst years. For the correx, we put in parenthesis the p-values computed using eq.(1). The *mortality index* is here the weighted mortality rate index defined in eq.(5) for ages between 25 to 50.

Indicator	US 1933-2010	UK 1922-2011	JP 1947-2012	FR 1880-2009	SW 1901-2011	AU 1921-2011
GDP:						
extreme	0.30 (55%)	−0.14 (20%)	−0.71 (23%)	−0.71 (10%)	−0.80 (6%)	0.12 (55%)
full sample	0.35	0.19	−0.48	−0.36	−0.32	0.11
Inflation						
extreme	0.39 (89%)	0.54 (91%)	−0.26 (59%)	−0.66 (18%)	0.19 (55%)	0.56 (92%)
full sample	−0.11	0.06	−0.36	−0.43	0.41	0.06
Stock						
extreme	−0.40 (24%)	0.85 (100%)	−0.57 (33%)	−0.39 (15%)	0.44 (80%)	0.65 (96%)
full sample	−0.09	−0.06	−0.44	−0.14	0.01	0.07
10Y Gov. Yield						
extreme	0.25 (77%)	0.30 (80%)	0.52 (100%)	−0.22 (22%)	0.02 (47%)	0.02 (84%)
full sample	0.10	0.13	−0.25	0.04	0.03	−0.18

C Lessons from the Spanish flu of 1918-1919 for the potential dependency between pandemic shocks and finance, by Philippe Trainar

Different ways may help us test the dependency between pandemic events and financial performances. One way to do it is by looking at econometrical correlations between both. The drawback of this method is that data are not available on a homogenous basis, over a sufficient period and at a sufficient granular level, especially at a monthly level. Most of the available data begin after 1918 and therefore exclude the last significant pandemic, i.e. the Spanish flu, this is true for statistics on deaths, GDP, stock market and interest rates for most countries. And when they are available, they are not available all at the same time and they are only available on a yearly basis, which is not accurate for testing for the Spanish flu as 1918 is not only a pandemic year but also a wartime and it is therefore impossible to disentangle yearly variations due to war and those due to pandemic. One needs monthly data for that, bearing in mind that the last deadly offensives took place in October 1918 and the armistice went in November.

As it appears clearly in Figure 1 presenting the weekly evolution of the rate of deaths in the UK in the second half of 1918 and beginning of 1919, the Spanish flu hit the UK in three waves. The first pandemic influenza wave appeared end of spring 1918, followed in rapid succession by much more fatal second and third waves in the fall and winter of 1918−1919, respectively. The timing of the hit was quite similar in the US as it appears in Figure 2 presenting the monthly evolution of the number of deaths caused by pneumonia over 1889-1920 in New York city.

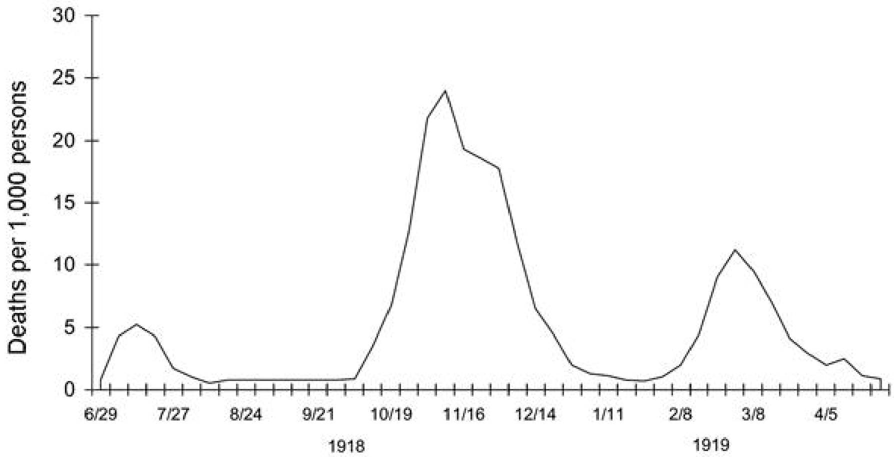

Figure 1: Death Rate in the UK during 1918-19

When looking at this data and at the data for the main world big cities (New York, London, Paris and Berlin) in Figure 3, it is clear that the pandemic shock has been concentrated from end of October to beginning of March, i.e. over 4 months, and that this shock was highly lethal, killing 2% of the infected persons compared to 0.15% for the first wave. 50% of the world population should have been infected. But, one should notice that the mortality rate has been widely fluctuating

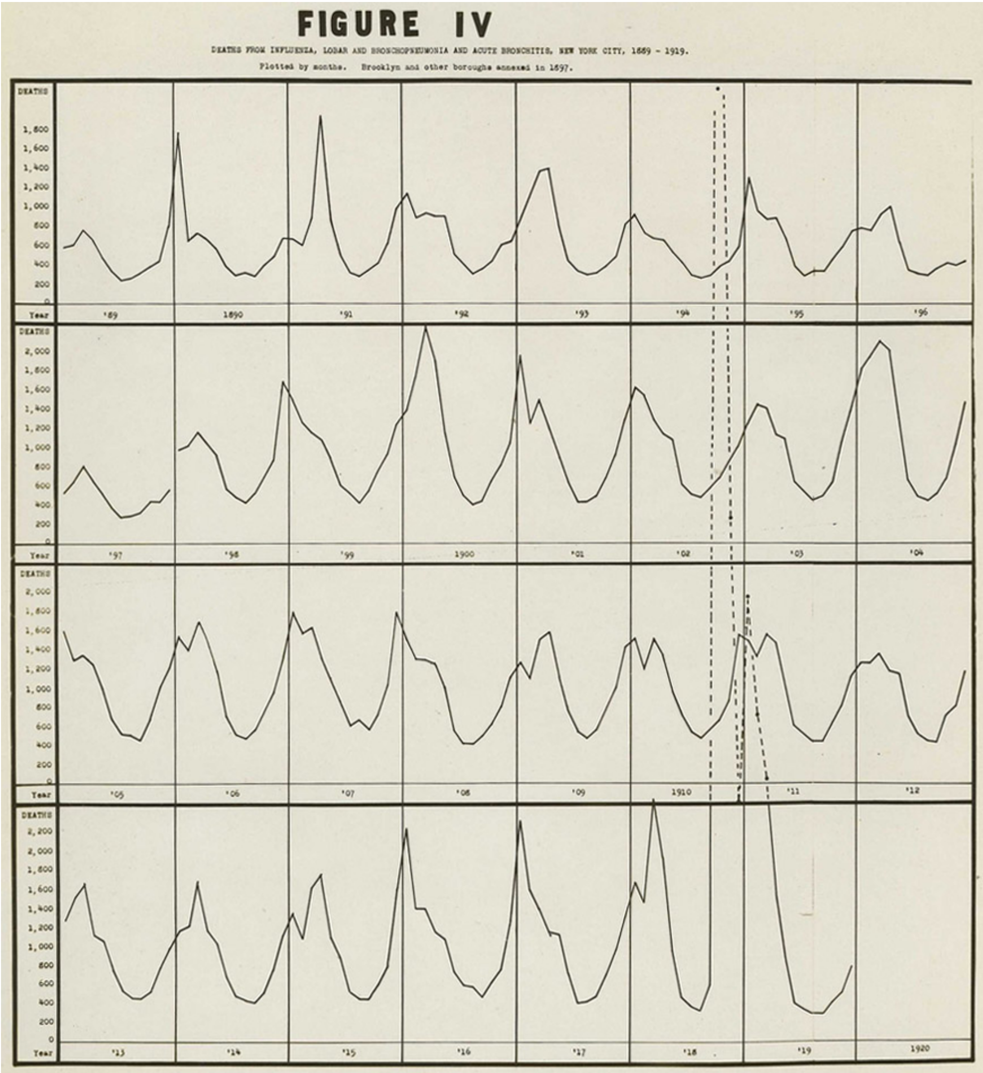

Figure 2: Number of deaths caused by pneumonia in NY city during 1889-1920

from one country to the other (for example, 25% of the population of Alaska and Samoa has been decimated).

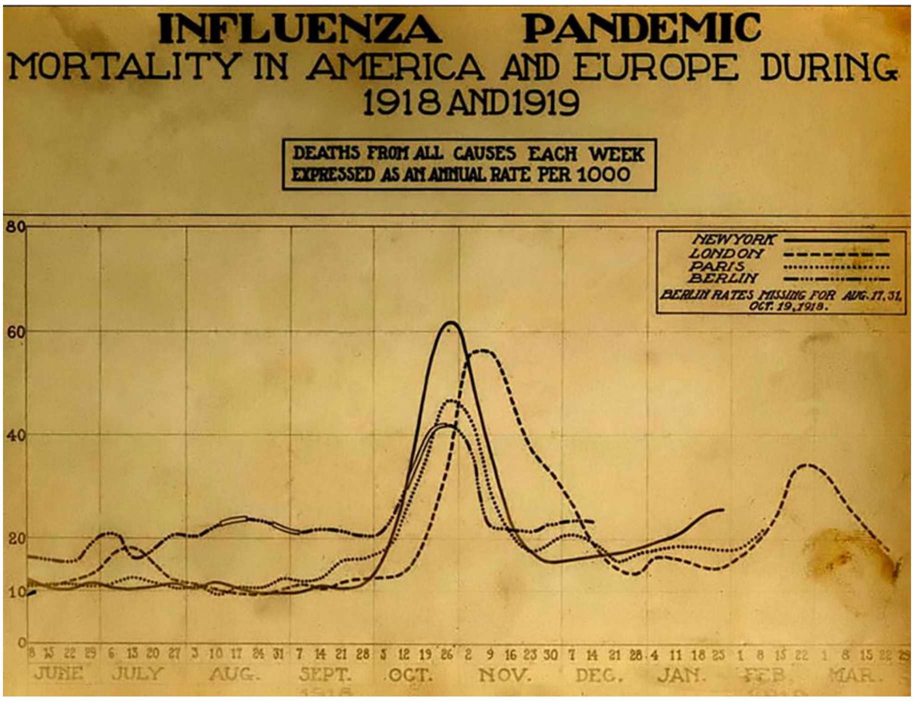

Figure 3: Mortality in the main world big cities during 1918-1919

If we concentrate on this period of 4 months and on the following months, one cannot distinguish a strong dependency between the pandemic shock and the evolution of the US stock market price, for which monthly data are available:

- comparison with a medium term trend of the US stock market, as estimated by an Hodrick-Prescott filter of power 2 and lambda 100, accurate for long term trend, points to a negative deviation which reaches a maximum of 4.5% and which lasts over 5 months (cf. Figure 4)
- comparison with a shorter term trend of the US stock market, as estimated by an Hodrick-Prescott filter of power 4 and lambda 6.25, points to a negative deviation which reaches a maximum of 2.5% and which lasts over 4 months (cf. Figure 5)

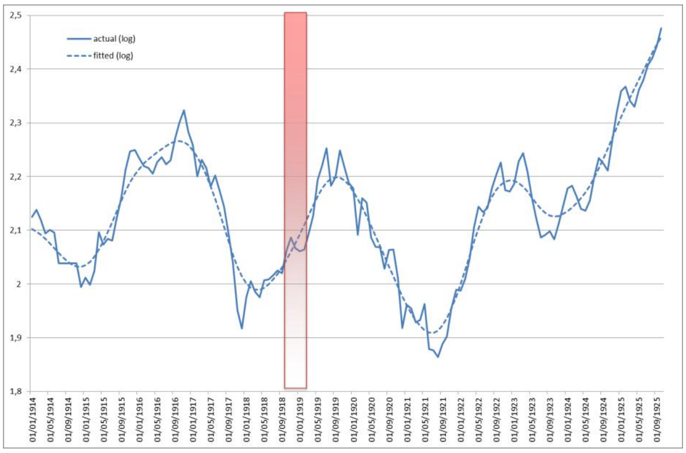

Figure 4: US stock market price compared to its medium term trend

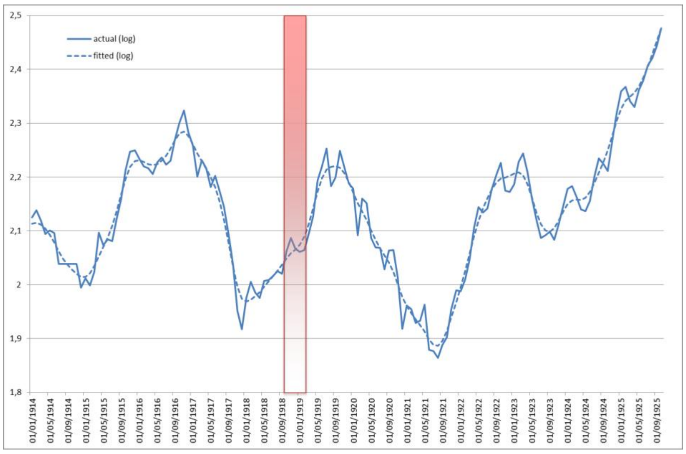

Figure 5: US stock market price compared to its short term trend

Concerning the interest rates, the picture is significantly different as can be seen on Figure 6: for the US as well as the UK, for which monthly data for the long term interest rates of the government bonds are available (10 years bonds in the US and consols in the UK), one can see a significant increase of the interest rate during this period and lasting until 1922, which reaches a maximum of 200 basis points in the US and 150 points in the UK in 1920-1921.

But, it very is difficult to really conclude from this move to a positive dependency between pandemic shocks and interest rates, for two reasons:

1. On one hand, such a dependency is totally counter-intuitive : one would have expected decreasing and not increasing interest rates in such circumstances
2. On the other hand, as can be seen from Figure 7, inflation had been jumping in the US at

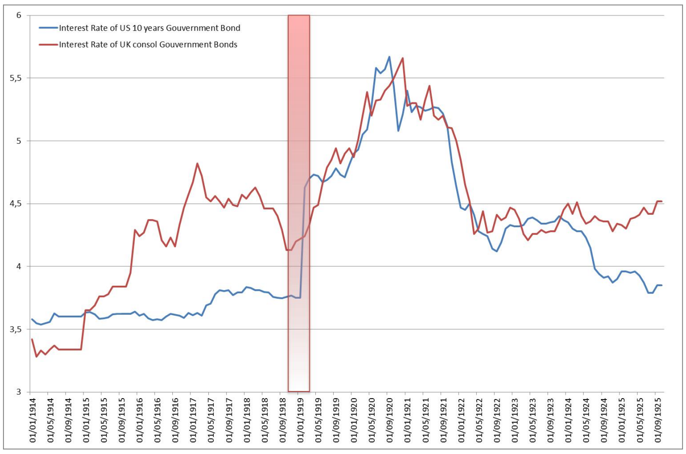

Figure 6: US 10 years government bonds and UK consols rates

double digit levels and interest rates increased immediately following the end of the war and the armistice

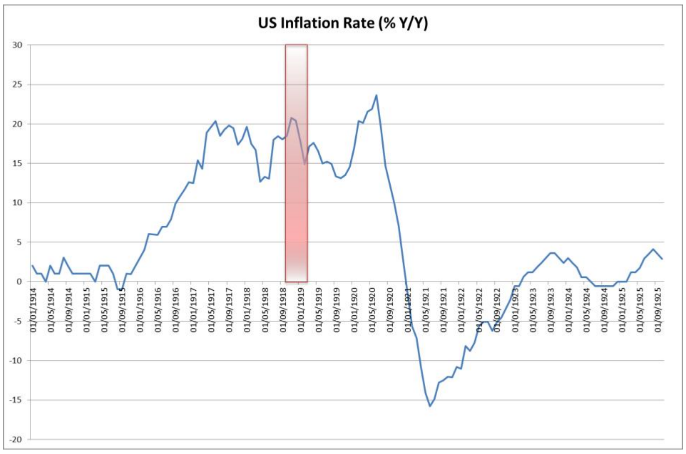

Figure 7: US inflation rate

At the same time, if the increase of the interest rates is not due to the pandemic shock, the deviation of the stock market from trend because of this shock should have been smaller than the one estimated above or even absent (the sudden increase of the US interest rate at the end of 1918 could explain most of the fall of the US stock market price observed in December and January).

In conclusion, there does not seem to be a statistically significant dependency between big pandemic shocks, such as the Spanish flu of 1918-1919, and financial performance over a one-year time horizon. Of course, 1918-1919 is a very specific period and the dependency might be overshadowed by the consequences of the end of the war. At the same time, the human consequences of the Spanish flu have been as dramatic in terms of deaths as those of the war so that, if they would have had significant consequences, this should have been visible in one way or the other.

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