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# Physica A

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## Coupling between death spikes and birth troughs. Part 2: Comparative analysis of salient features

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### h i g h l i g h t s

- Sudden death spikes produce birth troughs 9 months later.
- The relationship between spike and trough amplitudes is hyperbolic.
- This effect can also be identified on annual data.

#### a r t i c l e i n f o

*Article history:* Received 25 October 2017 Received in revised form 28 February 2018 Available online 17 April 2018

*Keywords:* Death rate Birth rate Shock Transfer function Seasonal pattern

#### a b s t r a c t

In part 1 we identified a coupling between death spikes and birth dips that occurs following catastrophic events such as influenza pandemics and earthquakes. Here we seek to characterize some of the key features of this effect. We introduce a transfer function defined as the amplitude of the birth trough (the output) divided by the amplitude of the death spike (the input). It has two salient features: (i) it is always smaller than one so is an attenuation factor and (ii) as a function of the amplitude of the death spike, it is a power law with exponent close to unity.

Since many countries do not publish monthly data, merely annual data, we attempt to extend the analysis to cover such data and how to identify the death–birth coupling. Finally, we compare the responses to unexpected death spikes and those to recurrent seasonal death peaks, such as winter death peaks.

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#### **1. Introduction**

The case-studies described in the previous paper  $(11)$ , thereafter referred to as "Paper 1") specified some of the conditions which must be fulfilled for this effect to exist. The fact that it took place for the H1N1 crisis in Hong Kong but not for the attack of 9/11 in New York led to the idea that it is not really the number of deaths which is the main determinant, but rather the total number of persons who experience an adverse shock in their living conditions.

In the present paper we have three objectives.

(1) In Paper 1 the coupling was represented as an input–output effect (see [Fig. 2a](#page--1-1)). It is therefore natural to measure how the transfer function of this system changes as a function of the magnitude of the initial death spike. In particular we wish to see if it is linear or nonlinear.

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<https://doi.org/10.1016/j.physa.2018.04.050> 0378-4371/© 2018 Elsevier B.V. All rights reserved.







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(2) Secondly, we wish to extend the analysis of the coupling effect to cases for which only annual data are available. This would represent a significant extension for monthly data are unavailable in many developing countries, either because they are collected but not sent to the central government or because the central government gets them but does not publish them.

(3) Apart from the exceptional death spikes due to special events, monthly mortality data display also seasonal peaks. The amplitudes of such peaks are country-dependent and in some countries they reach levels which are as high or even higher than the exceptional death spikes. It is therefore natural to compare their respective effect on birth numbers.

The first of these objectives will provide a real predictive power. Based on the number of deaths of an event, the law of the Bertillon effect will allow us to predict the birth rate reduction nine months later. As another implication, once a model will be proposed its first requirement will of course be to be consistent with the hyperbolic Bertillon law.

#### **2. Attenuation factor as a function of death spike amplitude**

In Paper 1, it was suggested that the main determinant is the number of persons who experience an adverse shock in their living conditions. Unfortunately, in many cases this number is not well defined. For instance the measure of the incidence of a disease is highly dependent upon the criterion that is used:

- The number of persons hospitalized gives a low measure of incidence.
- A broader measure of incidence is through the number of working days lost to sickness in the labor market.

However, statistical data corresponding to these criteria are rather sparse and not comparable across a set of countries. In the case of earthquakes we suggested that the shock on survivors could be measured through the number of ''damaged houses'' but this latter notion is itself a matter of appraisal.

For all these reasons the number of deaths remains the most convenient parameter for it has a clear significance and is widely available in vital statistical records.

#### *2.1. Method*

As for all time series which show a seasonal pattern we need to resolve how to handle it. The methods that we will use successively rely on two different conceptions of the phenomenon under consideration.

#### *2.1.1. All inclusive conception (1)*

In the first conception we consider the death spike as being of the same nature as the seasonal fluctuations. In other words it is seen as a seasonal fluctuations which just happens to be somewhat higher than the others. In this conception it would not make sense to separate the two effects. This means that we measure the amplitude of the death spike (and similarly for the birth trough) just ''as it is''. The beginning of the spike will be defined as the month where the number of deaths starts to increase after having been decreasing or flat. Similarly, the end of the spike will be the month where the deaths start to level off or to increase. Naturally, even if there is a small local dip in the upward phase or a local surge in the downward phase we do not wish them to be taken into account. That is why we perform a 3-point centered moving average before implementing the previous procedure.

#### *2.1.2. Seasonal fluctuations seen as noise (2)*

In the second conception in which one considers that the death spike is of a different nature than the seasonal fluctuations, the challenge is to remove the seasonal variations in the ''best'' possible way. In principle, the way to do that seems fairly evident and consists in dividing the monthly deaths of year  $y_0$  by the seasonal profile that we denote by  $P_s$  (it is a set of 12 numbers). But how should the seasonal profile be defined? The answer depends upon the characteristics of the seasonal pattern. The simplest way is to take the monthly death profile of the year *y*−<sup>1</sup> preceding *y*0, in other words: *P<sup>s</sup>* = *D*(*y*−1). The main advantage of such a choice is the fact that in case there is a drift of the seasonal profile in the course of time, the year closest to  $y_0$  will be the most appropriate.

A possible drawback of taking *D*(*y*−1) is the fact that, as a single year, it may differ from the average seasonal pattern. Instead of taking only one year it is tempting to think that an average over several years would better approximate *P<sup>s</sup>* . Is that true?

If the inter-annual statistical fluctuations of seasonal variations are small, then the average of *n* years will indeed converge toward a reasonable seasonal pattern. However, one should observe that in such a case *D*(*y*−1) differs little from the average and is also a good choice therefore.

On the contrary, if from year to year there are large random changes in the monthly pattern, then an average of several years will be almost flat and the more years one takes the flatter it will become. $^1\,$  $^1\,$  $^1\,$  Such an average will be useless therefore and in such a case *D*(*y*−1) will probably be the best choice as being close to *y*0.

- In summary we retain two procedures:
- (1) Scaling the spikes and troughs just ''as they are''.
- (2) Scaling them after dividing them by *D*(*y*−1) and *B*(*y*−1) respectively.
- In what follows we will try successively the two procedures.

<span id="page-1-0"></span> $1$  In order to discuss this point theoretically one would have to know the statistical frequency functions of the deaths (or births) in each months and also the interdependence of deaths in neighboring months. The statement that the average of several years tends to become level relies on tests performed on Japanese death data.

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