Gompertz Processes: A Theory of Ageing

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Abstract

Ageing is a accelerating failure process that is universal to all biological systems. Motivated by considering infinitesimal stochastic accelerations of time, we hypothesize a general explanation for the emergent determinism of ageing processes in the theory of Gompertz processes: Poisson processes subordinated by integrated Geometric Brownian motion.

1 Preliminaries

Basic science experiments in biology have ubiquitously observed that organisms respond to environmental stresses, including communicable diseases and exposures to toxins, with an acceleration a in their failure time $ah(at)$, where $h(t)$ is the unperturbed hazard rate of the failure event. Outside of the controlled setting of a laboratory the environmental stresses occur stochastically, resulting in a stochastic sequence of accelerations a_n of the organism's metabolic time. The stochastic accelerations can either increase the rate of failure $a_n > 1$, an exacerbation of the stresses, or decrease the rate of failure $a_n < 1$, an alleviation from the stresses. However, even in the controlled setting of a laboratory it is experimentally challenging to directly measure the stochastically accelerated metabolic time of the organism, instead we only have access to the failure events measured at bare time units. Thus a theory of ageing must study the subordination of the failure time by a stochastically accelerated metabolic time.

Over the course of an organism's lifetime it will encounter exacerbations and alleviations that stochastically accelerate $a_n, \ldots, a_0 = 1$ metabolic time at times $t_n, \ldots, t_0 = 0$. Furthermore, because the stochastic accelerations are all positive $a_i > 0$ for each stochastic acceleration we can find a finite real valued generator $w_n, \ldots, w_0 = 0$ such that $a_i = e^{w_i}$. It follows that the stochastically accelerated metabolic time y_{t_n} at time t_n is the sum of the products of the stochastic accelerations up to time t_{n-1} and the elapsed bare time steps $t_i - t_{i-1}$:

$$y_{t_n} = \sum_{i=1}^{n} e^{\sum_{j=0}^{i-1} w_j} (t_i - t_{i-1}) \tag{1}$$

Provided no great explosions of acceleration occur in any small time scale, like say when an actual explosion occurs, the generators w_i will become infinitesimal on the same order as the bare time steps become infinitesimal $t_i - t_{i-1} \to 0$:

$$\mathcal{O}(w_i) = \mathcal{O}(t_i - t_{i-1}) \tag{2}$$

The sum of products then becomes a stochastic process Y_t that is an integral of a random geometric infinitesimal generator process e^{W_u}:

$$Y_t = \int_0^t e^{W_u} du \tag{3}$$

This asymptotic argument is essentially the continuous part of the Kolmorgorov's characterization of stochastic processes as being composed, in bounded time, of either a finite number of discrete jumps or an infinite number of continuous changes. If we assume as a first approximation that the exacerbations and alleviations, and their respective stochastic accelerations, are independent and stationary over time then by the Lévy-Khintchine characterization the only infinitesimal generator of stochastically accelerated metabolic time that is Lévy and continuous *"jump free"* is Brownian motion W_u. The stochastically accelerated metabolic time is better known as integrated geometric Brownian motion.

2 Gompertz

Motivated by the preceding heuristic derivation we formally define the Gompertz process on time $t \geq 0$.

Definition 1 (Gompertz Process)**.** A Gompertz process G_t is a subordinated Poisson process N_t, with rate λ, where the subordinating process is integrated geometric Brownian motion Y_t, with drift μ and diffusion σ:

$$G_t = N_{Y_t} \tag{4}$$

given:

$$\begin{aligned} Y_t &= \int_0^t X_s ds &(5)\\ &= \int_0^t e^{\mu s + \sigma W_s} ds &(6) \end{aligned}$$

Phenomenologically the finite real stochastic process $\mu t + \sigma W_s$ is the infinitesimal acceleration at time t that generates a non-negative geometric stochastic process X_t of accumulated accelerations up to time t and whose integral Y_t is a strictly increasing stochastically accelerated metabolic time up to time t.

From the definition of the Gompertz process G_t conditioning on the history of a sample path of integrated geometric Brownian motion Y_t yields a conditional Poisson process:

$$\mathbb{P}[G_t = n \| Y_t] = \frac{(\lambda Y_t)^n}{n!} e^{-\lambda Y_t} \tag{7}$$

$$\mathbb{E}[G_t \| Y_t] = \lambda Y_t \tag{8}$$

Dual to conditioning integrated geometric Brownian motion, conditioning on the Gompertz process estimates the elapsed stochastically accelerated metabolic time:

$$\mathbb{P}\left[Y_t \leq y \| \, G_t\right] = \int_0^{\lambda y} \frac{u^{G_t-1} e^{-u}}{(G_t-1)!} du \tag{9}$$

$$\mathbb{E}\left[Y_t \| \, G_t\right] = \frac{G_t}{\lambda} \tag{10}$$

Reflecting that integrated geometric Brownian motion Y_t is truly measuring the elapsed stochastically accelerated metabolic time.

To start our exploration of the rich subtleties of the Gompertz process we will briefly review the properties of integrated geometric Brownian motion which are salient to developing our theory. This is by no means a comprehensive compendium. Much of the material I will cover has been deeply and thoroughly explored in the quantitative finance literature in the theory of pricing Asian options, and the stochastic processes syllabus on subordinated Poisson processes, usually in the context of deriving the characteristic function of the subordinating process.

Our first observation is that the increments of Y_t can be factored by its carrier process X_t, for times $t > s$:

$$\mathbb{P}\left[Y_t - Y_s\right] = \mathbb{P}\left[X_s\right] \mathbb{P}\left[Y_{t-s}\right] \tag{11}$$

where the process X_s is independent of the process Y_{t-s}. Phenomenologically the increments of $Y_t - Y_s$ are equivalent to a process that starts with acceleration X_s. Analogous to the Fundamental Theorem of Arithmetic this factorization allows us to reach many useful inferences; for example we can immediately observe that for times $t > s$:

$$\mathbb{E}\left[(Y_t - Y_s)^n \| \, X_s\right] = X_s^n \, \mathbb{E}\left[Y_{t-s}^n\right] \tag{12}$$

We will liberally exploit this technique of arbitraging the stochastically accelerated metabolic time Y_t against the accumulated stochastic accelerations X_t to reduce expectations down to the well known standard terms for X_t and Y_t:

$$\mathbb{E}\left[X_t^n\right] = e^{\left(n\mu + n^2\sigma^2/2\right)t} \tag{13}$$

$$\mathbb{E}\left[Y_t\right] = \frac{e^{\left(\mu+\sigma^2/2\right)t} - 1}{\mu + \sigma^2/2} \tag{14}$$

Note that in the last equation we have implicitly invoked the Fubini-Tonelli Theorem to switch the order of integration, and will broadly continue to use this theorem throughout this work.

Lemma 1 (Acceleration Lemma)**.** *The expectation of non-negative integer powers $n \geq 0$ of the carrier process of geometric Brownian motion X_t conditioned on integrated geometric Brownian motion Y_t are given by:*

$$\mathbb{E}\left[X_t^n \| \, Y_t\right] = \frac{\mathbb{E}\left[X_t^n\right]}{\mathbb{E}\left[Y_t^n\right]} Y_t^n \tag{15}$$

Proof. We proceed by induction on n.

1. For $n = 0$ clearly $\mathbb{E}\left[X_t^0 \| \, Y_t\right] = 1$
2. Now assume that up to n the relation holds.
3. For $u < t$ consider the integrable function
$$f(u,t,y) = \mathbb{E}\left[X_u X_t^n \| \, Y_t = y\right] \tag{16}$$
4. It follows from the Fubini-Tonelli Theorem and the induction assumption that for n the integral is
$$\int_0^t f(u,t,y)\, du = y^{n+1} \frac{\mathbb{E}\left[X_t^n\right]}{\mathbb{E}\left[Y_t^n\right]} \tag{17}$$
5. Thus by the Fundamental Theorem of Calculus the integrand has the decomposition $f(u,t,y) = y^{n+1} f(u,t)$
6. By the Law of Conditional Expectations we have
$$\begin{aligned} \mathbb{E}\left[X_u X_t^n\right] &= \mathbb{E}\left[\mathbb{E}\left[X_u X_t^n \| \, Y_t\right]\right] && (18) \\ &= f(u,t)\, \mathbb{E}\left[Y_t^{n+1}\right] && (19) \end{aligned}$$
7. Which immediately yields the decomposed integrand as
$$f(u,t) = \frac{\mathbb{E}\left[X_u X_t^n\right]}{\mathbb{E}\left[Y_t^{n+1}\right]} \tag{20}$$
8. Finally taking $u = t$ yields the desired result
$$\begin{aligned} \mathbb{E}\left[X_t^{n+1} \| \, Y_t\right] &= f(s,t,t)\, Y_t^{n+1} && (21) \\ &= \frac{\mathbb{E}\left[X_t^{n+1}\right]}{\mathbb{E}\left[Y_t^{n+1}\right]} Y_t^{n+1} && (22) \end{aligned}$$

□

A simple corollary follows from a nearly trivial derivation.

Corollary 1 (Counterpoint Corollary)**.** *For a times $t > s$ we have the following conditional expectation:*

$$\mathbb{E}\left[Y_t^n \| \, Y_s\right] = \frac{\mathbb{E}\left[Y_t^n\right]}{\mathbb{E}\left[Y_s^n\right]} Y_s^n \tag{23}$$

Proof. Factoring and applying the previous lemma:

$$\begin{aligned} \mathbb{E}\left[Y_t^n \| \, Y_s\right] &= \mathbb{E}\left[X_s^n \| \, Y_s\right] \mathbb{E}\left[Y_{t-s}^n\right] && (24) \\ &= \frac{\mathbb{E}\left[Y_{t-s}^n\right] \mathbb{E}\left[X_s^n\right]}{\mathbb{E}\left[Y_s^n\right]} Y_s^n && (25) \\ &= \frac{\mathbb{E}\left[Y_t^n\right]}{\mathbb{E}\left[Y_s^n\right]} Y_s^n && (26) \end{aligned}$$

□

Even with the factorization observation we are still in need of a means of reducing the expectation of the powers Y_t^n. A small lemma suffices to provide the means of finding powers:

Lemma 2 (Recursion-Convolution Lemma)**.** *The expectation of non-negative integer powers $n \geq 0$ of integrated geometric Brownian motion Y_t is given by:*

$$\mathbb{E}\left[Y_t^n\right] = n \int_0^t \mathbb{E}\left[X_u^n\right] \mathbb{E}\left[Y_{t-u}^{n-1}\right] du \tag{27}$$

Proof. Expanding the expectant as a multi-variable integral we have, applying th Fubini-Tonelli Theorem we have, and then factoring we have:

$$\begin{aligned} \mathbb{E}\left[Y_t^n\right] &= \int_0^t \cdots \int_0^t \mathbb{E}\left[X_t^n\right] du_1 \ldots du_n & (28) \\ &= \binom{n}{1} \int_0^t \mathbb{E}\left[X_u \left(Y_t - Y_u\right)^{n-1}\right] du & (29) \\ &= n \int_0^t \mathbb{E}\left[X_u^n\right] \mathbb{E}\left[Y_{t-u}^{n-1}\right] du & (30) \end{aligned}$$

□

The recursion-convolution lemma relates the moments of integrated geometric Brownian motion through a linear operator, and like all good linear operators this relationship deserves a uniqueness constraint.

Corollary 2 (Uniqueness Corollary)**.** *If two sequences of functions $f_t^{(n)}$ and $g_t^{(n)}$ of time t satisfy the recursion-convolution relation and $f_t^{(0)} = g_t^{(0)} = 1$ then $f_t^{(n)} = g_t^{(n)}$ for all n.*

Proof. We proceed with induction on n

1. By assumption for $n = 0$ functions are equal.

2. Now assume that up to n the functions are equal.

3. Taking the difference between the functions at $n + 1$ we have

$$\begin{aligned} f_t^{(n+1)} - g_t^{(n+1)} &= \int_0^t \mathbb{E}\left[X_u^n\right] \left(f_{t-u}^{(n)} - g_{t-u}^{(n)}\right) du & (31) \\ &= 0 & (32) \end{aligned}$$

□

With the recursion-convolution lemma in hand we have the sufficient tools required to estimate all the usual statistics involving powers of Y_t, including the expectation, variance, and covariances.

3 Martingale

By our counterpoint corollary the amortized integrated geometric Brownian motion:

$$\hat{Y}_t = \frac{Y_t}{\mathbb{E}\left[Y_t\right]} \tag{33}$$

forms a martingale, so that for times $t > s$:

$$\mathbb{E}\left[\hat{Y}_t \middle\| \hat{Y}_s\right] = \hat{Y}_s \tag{34}$$

We can deduce that the amortized Gompertz process:

$$\hat{G}_t = \frac{G_t}{\mathbb{E}\left[Y_t\right]} \tag{35}$$

is a martingale, so that for times $t > s$:

$$\mathbb{E}\left[\hat{G}_t \middle\| \hat{G}_s\right] = \hat{G}_s \tag{36}$$

This allows us to leverage optional stopping time theorems to evaluate expectations of stopped versions of Gompertz processes.

4 Markov

Even though amortized integrated geometric Brownian motion $\hat{Y}_t$ is a martingale, integrated geometric Brownian motion Y_t is a 2 step Markov process, and thus the increments $Y_t - Y_s$, with $t > s$ are Markov. To verify this consider the sequence of bare times $0 = t_0 < \cdots < t_{n+1} = t$, and accelerated times $0 = y_0 < \cdots < y_{n+1} = y$, working through the conditional probability we have:

$$\begin{aligned}
&\mathbb{P}\left[Y_{t_{n+1}} - Y_{t_n} = y_{n+1} - y_n \| Y_{t_n} - Y_{t_{n-1}} = y_n - y_{n-1}, \ldots, Y_{t_1} - Y_{t_0} = y_1 - y_0\right] \\
&\quad = \int_0^\infty \int_0^\infty \mathbb{P}\left[X_{t_n - t_{n-1}} = \frac{u}{v} \frac{y_{n+1} - y_n}{y_n - y_{n-1}}\right] \\
&\qquad \cdot \mathbb{P}\left[Y_{t_n - t_{n-1}} = u\right] \\
&\qquad \cdot \mathbb{P}\left[Y_{t_{n+1} - t_n} = v\right] du dv \qquad (37) \\
&\quad = \mathbb{P}\left[Y_{t_{n+1}} - Y_{t_n} = y_{n+1} - y_n \| Y_{t_n} - Y_{t_{n-1}} = y_n - y_{n-1}\right] \qquad (38)
\end{aligned}$$

We can conveniently derive from the martingale the conditional expectation of the increment for a triple of times $t_1 > t_0 > t_{-1}$:

$$\mathbb{E}\left[Y_{t_1} - Y_{t_0} \| Y_{t_0} - Y_{t_{-1}}\right] = \frac{\mathbb{E}\left[Y_{t_1} - Y_{t_0}\right]}{\mathbb{E}\left[Y_{t_0} - Y_{t_{-1}}\right]} \left(Y_{t_0} - Y_{t_{-1}}\right) \tag{39}$$

In practice we cannot directly measure the stochastically accelerated metabolic time Y_t instead we have access to the stopping times T_n of the passages $G_{T_n} = n$ of the Gompertz process.

To study the Markov properties of the stopping times of the passages of the Gompertz process we revisit the recovery of the Poisson process from the Gompertz process by conditioning on the history of the sample path of integrated geometric Brownian motion. By differentiating the subordinated cumulative distribution of a single stopping time we have the conditional probability distribution:

$$\mathbb{P}\left[T_n = t \| \, Y_{T_n}\right] = \frac{\mathbb{E}\left[X_t\right]}{\mathbb{E}\left[Y_t\right]} \frac{(\lambda Y_t)^n}{(n-1)!} e^{-\lambda Y_t} \tag{40}$$

Finding a closed form for the distribution of the stopping times of the passages of the Gompertz process will require a deeper understanding of the characteristic function of integrated geometric Brownian motion, which we will develop later. In the meantime there are many fruits to be plucked from a study of stopping times of the passages of the Gompertz process.

The central statistic of study in the longitudinal analysis of biological systems is the latency $T_{1+G_t} - T_{G_t} = T_{1+G_t} - t$ between consecutive stopping times of the passages of the Gompertz process. Due to immortal time bias *"we cannot see indefinitely into the past"* we have subordinated the stopping times T_{n+G_t} of the passages of the Gompertz process by the increments of the Gompertz process $n + G_t$ from a sentinel event G_t. In practice observational studies, particularly in clinical research and epidemiology, are only able to observe consecutive passages of the Gompertz process from a fixed sentinel event without the knowledge of how many events have occurred before the sentinel event.

From the preceding probability density we can immediately deduce the tail probability and hence the expectation of the latency $s > 0$ conditioned on a sentinel event at time $t > 0$:

$$\mathbb{P}\left[T_{1+G_t} - T_{G_t} \geq s \| \, T_{G_t} = t\right] = \mathbb{E}\left[e^{-\lambda X_t Y_s}\right] \tag{41}$$

$$\mathbb{E}\left[T_{1+G_t} - T_{G_t} \| \, T_{G_t} = t\right] = \int_0^\infty \mathbb{E}\left[e^{-\lambda X_t Y_s}\right] ds \tag{42}$$

where Y_s is the increment process independent of the acceleration X_t at the start of the increment.

Remarkably the stopping times of the passages for the Gompertz process are Markov, even though the stochastically accelerated metabolic time of integrated geometric Brownian motion is only Markov in its increments. Specifically knowledge of the age $t_0 > 0$ at a sentinel event G_{t_0} in the history of the Gompertz process is sufficient to determine the distribution of the latency $t > 0$ to next event $T_{1+n+G_{t_0}}$. To see this consider the subordinated stopping times $T_{n+G_{t_0}} = t_n, \ldots, T_{G_{t_0}} = t_0$, the cumulative probability of the latency conditioned of the previous events is:

$$\begin{aligned}
&\mathbb{P}\left[T_{1+n+G_t} - T_{n+G_t} \geq t \| \, T_{n+G_{t_0}} = t_n, \ldots, T_{G_{t_0}} = t_0\right] \\
&\quad = \mathbb{E}\left[e^{-\lambda(Y_{t+t_n} - Y_{t_n})} \middle\| \, T_{n+G_{t_0}} = t_n, \ldots, T_{G_{t_0}} = t_0\right] && (43)\\
&\quad = \mathbb{E}\left[e^{-\lambda X_{t_n} Y_t}\right] && (44)\\
&\quad = \mathbb{P}\left[T_{1+G_{t_n}} - T_{G_{t_n}} \geq t \| \, T_{G_{t_n}} = t_n\right] && (45)
\end{aligned}$$

where Y_t is the increment process independent of the acceleration X_{t_n} at the start of the increment.

Given that the stopping times of consecutive passages of the Gompertz process are Markov we consider the covariance of the latency between consecutive events $T_{2+G_t}, T_{1+G_t}, T_{G_t}$ conditioned on the sentinel event $T_{G_t} = t$:

$$\begin{aligned}
&\mathbb{C}\mathrm{ov}\left[T_{2+G_t} - T_{1+G_t}, T_{1+G_t} - T_{G_t} \| \, T_{G_t} = t\right] \\
&\quad = \int_0^\infty \int_0^\infty \mathbb{E}\left[e^{-\lambda X_{t+v} Y_u}\right] \mathbb{E}\left[\lambda v X_v e^{-\lambda X_t Y_v}\right] dv du \\
&\qquad - \int_0^\infty \mathbb{E}\left[\lambda X_t Y_u e^{-\lambda X_t Y_u}\right] du \int_0^\infty \mathbb{E}\left[e^{-\lambda X_t Y_u}\right] du && (46)
\end{aligned}$$

where all the stochastic processes are independent except the final acceleration X_v and the increment Y_v.

The Gompertz process introduces an irreducible exponential dependence on age *"older organisms are red-shifted with respect to younger organisms"* that cannot be removed or linearized by a coordinate transform, analogous to the Hubble constant which describes the intrinsic expansion of space-time and for which no coordinate transform can remove the intrinsic red-shift of space-time. We can concretely predict that the age of an organism introduces a correlation within the latencies between consecutive events, and that this correlation can be fully accounted for by conditioning on the age of the organism at the sentinel event.

Our observations of the Gompertz process have a serious consequence. Every single longitudinal experiment that has studied outcomes whose latencies are on the same timescale as the lifespan of the investigated organism has introduced spurious correlations into their longitudinal analysis of event latency, which are purely an artefact of the failing to account for the exponential age dependence of the Gompertz process. Fortunately, the majority of the studies of biological systems have either been cross-sectional or of short enough duration that the hazard of the Gompertz process is approximately constant over the timescale of the experiment on the organism.

5 Lévy

Integrated geometric Brownian motion Y_t and its carrier process of geometric Brownian motion X_t can be embedded into the Lie group of 2×2 upper triangular matrices $\mathfrak{h}_2$ by means of the factorization observed earlier, so that the increments are independent under matrix multiplication, for times $t > s$:

$$\begin{bmatrix} 1 & Y_t \\ 0 & X_t \end{bmatrix} = \begin{bmatrix} 1 & Y_{t-s} \\ 0 & X_{t-s} \end{bmatrix} \begin{bmatrix} 1 & Y_s \\ 0 & X_s \end{bmatrix} \tag{47}$$

where the increment processes of Y_{t-s} and X_{t-s} are independent of the processes Y_s and X_s. It follows that the infinitesimal generator of the matrix exponential map into the group is the sub-algebra of the Lie algebra of upper triangular matrices $\mathfrak{h}_2$ consisting of first column zero matrices:

$$\exp\left(\frac{\mu t + \sigma W_t}{X_t - 1} \begin{bmatrix} 0 & Y_t \\ 0 & X_t - 1 \end{bmatrix}\right) = \begin{bmatrix} 1 & Y_t \\ 0 & X_t \end{bmatrix} \tag{48}$$

This Lie sub-algebra has the basis commutator:

$$\left[\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right] = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \tag{49}$$

As we will see next this raises the prospect of a deep connection between the adjoint derivative of the exponential map and stochastic differential equations.

6 Fokker-Planck

The upper triangular Lévy process of integrated geometric Brownian motion satisfies the stochastic differential equation:

$$d\begin{bmatrix} 1 & Y_t \\ 0 & X_t \end{bmatrix} = \begin{bmatrix} 0 & X_t \\ 0 & \left(\mu + \sigma^2/2\right) X_t \end{bmatrix} dt + \begin{bmatrix} 0 & 0 \\ 0 & \sigma X_t \end{bmatrix} dW_t \tag{50}$$

$$= \left(\begin{bmatrix} 0 & 1 \\ 0 & \mu + \sigma^2/2 \end{bmatrix} dt + \begin{bmatrix} 0 & 0 \\ 0 & \sigma \end{bmatrix} dW_t\right) \begin{bmatrix} 1 & Y_t \\ 0 & X_t \end{bmatrix} \tag{51}$$

It follows from Fokker-Planck that the probability density of the joint process $p = \mathbb{P}\left[Y_t = y, X_t = x\right]$ satisfies the partial differential equation:

$$\frac{\partial p}{\partial t} = -\frac{\partial}{\partial x}\left(\mu + \frac{\sigma^2}{2}\right) xp - \frac{\partial}{\partial y} xp + \frac{\partial^2}{\partial x^2}\frac{\sigma^2}{2} x^2 p \tag{52}$$

We can restate this as an Eigen evolution equation:

$$\frac{\partial p}{\partial t} + \left(\mu + \frac{3}{2}\sigma^2\right) x\frac{\partial p}{\partial x} + x\frac{\partial p}{\partial y} - \frac{\sigma^2}{2} x^2 \frac{\partial^2 p}{\partial x^2} = \left(-\mu + \frac{\sigma^2}{2}\right) p \tag{53}$$

Marginalizing over the probability of X_t and applying the acceleration lemma yields the first order partial differential equation for the distribution of Y_t:

$$\frac{\mathbb{E}\left[Y_t\right]}{\mathbb{E}\left[X_t\right]}\frac{\partial p}{\partial t} - y\frac{\partial p}{\partial y} = p \tag{54}$$

Which by trial solution of separation of variables has the general solution:

$$p = \mathbb{E}\left[Y_t\right] f_{\mu,\sigma}\left(y\,\mathbb{E}\left[Y_t\right]\right) \tag{55}$$

for any analytic $f_{\mu,\sigma}$ dependent on the drift and diffusion of the carrier process X_t. Note that we are offloading the dimensional analysis into the analytic function.

7 Hazard Rate

Consider the first passage stopping time T_1 of the Gompertz process G_t, its tail distribution is the characteristic function of Y_t:

$$\mathbb{P}\left[T_1 \geq t\right] = \mathbb{E}\left[e^{-\lambda Y_t}\right] \tag{56}$$

Thus the hazard rate h of T_1:

$$h = \mathbb{P}\left[T_1 = t \| \, T_1 \geq t\right] \tag{57}$$

satisfies the partial differential Eigen equation:

$$\frac{\mathbb{E}\left[Y_t\right]}{\mathbb{E}\left[X_t\right]} \frac{\partial h}{\partial t} - \lambda \frac{\partial h}{\partial \lambda} = \left(\frac{\mathbb{E}\left[Y_t\right]}{\mathbb{E}\left[X_t\right]}\right)^2 \left(\frac{\partial}{\partial t} \frac{\mathbb{E}\left[X_t\right]}{\mathbb{E}\left[Y_t\right]}\right) h \tag{58}$$

Which by trial solution of separation of variables has the general solution:

$$h = \lambda^2 \, \mathbb{E}\left[X_t\right] \mathbb{E}\left[Y_t\right] g_{\mu,\sigma}\left(\lambda \, \mathbb{E}\left[Y_t\right]\right) \tag{59}$$

for any analytic $g_{\mu,\sigma}$ dependent on the drift and diffusion of the carrier process X_t. Taking the limit to deterministic subordination yields the constraints on $g_{\mu,\sigma}$:

Table 1: Sequential Boundary Conditions

Boundary	Condition	Removes
$\sigma = 0$	$h = \lambda e^{\mu t}$	diffusion
$\mu = 0$	$h = \lambda$	then drift
$\lambda = 0$	$h = 0$	finally jumps

Sequential boundary conditions on the hazard rate h derived from the limits to deterministic subordination.

From the boundary conditions we can immediately deduce that in the deterministic limit of $\sigma \to 0$ we have:

$$g_{\mu,\sigma}\left(x\right) \xrightarrow{\sigma=0} \frac{1}{x} \tag{60}$$

However this alone cannot be the solution as it results in the characteristic function in λ of a purely deterministic Y_t. Equating the general solution for the hazard rate to the Laplace of the Fokker-Planck solution yields the implicit equation in $f_{\mu,\sigma}$ and $g_{\mu,\sigma}$:

$$-\frac{\partial}{\partial t} \ln \int_0^\infty e^{\frac{\lambda u}{\mathbb{E}\left[Y_t\right]}} f_{\mu,\sigma}\left(u\right) du = \lambda^2 \, \mathbb{E}\left[X_t\right] \mathbb{E}\left[Y_t\right] g_{\mu,\sigma}\left(\lambda \, \mathbb{E}\left[Y_t\right]\right) \tag{61}$$

Dimensional analysis provides an inference for a solution, which remains an open problem:

Proposition 1 (Gompertz Anomaly)**.** *The analytic function $g_{\mu,\sigma}$ is simply the exponential divided by its argument, so that the hazard rate h is given by:*

$$h = \lambda \, \mathbb{E}\left[X_t\right] e^{\frac{\lambda\sigma^2/2}{\mu+\sigma^2/2}\, \mathbb{E}[Y_t]} \tag{62}$$

Proof. The parity multiplied derivatives of the exponential of the integral of the hazard rate satisfies the recursion-convolution lemma, generating the moments of Y_t, and hence is the characteristic function of Y_t. □

8 Discussion

In most circumstances λ is the new born infant mortality due to ageing alone, and is less than 1 in 32000 person-years. As such the hazard rate is very close to the original hazard rate observed by Gompertz. Intuitively, when $\mu \ggg \sigma^2/2$ the process becomes approximately deterministic due to the large impact of the drift.

Conversely, the central conjecture in the preliminary material is that ageing is driven by stochastic accelerations, requiring that the drift vanish $\mu = 0$. In this case the anomalous Gompertz hazard rate simplifies to:

$$h = \lambda e^{t\sigma^2/2} e^{\lambda \frac{e^{t\sigma^2/2}-1}{\sigma^2/2}} \tag{63}$$

We have observed the anomalous Gompertz hazard rate in mortality rates in Alberta while conducting the Hazard Rate Zoo experiment. Specifically when we remove the dominate exponential process of a doubling of mortality every 7 years from an infant mortality of 1 in 32000 person-years:

$$h = \frac{2^{t/7}}{32000} e^{\frac{7\left(2^{t/7}-1\right)}{32000 \ln 2}} \tag{64}$$

there remains a residual anomalous growth in mortality with ageing, reflecting the higher order affect of the stochastic accelerations.