

MARKOV MORTALITY MODELS: IMPLICATIONS OF QUASISTATIONARITY AND VARYING INITIAL DISTRIBUTIONS

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ABSTRACT. This paper explains some implications of markov-process theory for models of mortality. We show, on the one hand, that an important qualitative feature which has been found in certain models — the convergence to a “mortality plateau” — is a generic consequence of the convergence to a “quasistationary distribution”, which has been explored extensively in the mathematical literature. This serves not merely to free these results from some irrelevant specifics of the models, but also to offer a new explanation of the convergence to constant mortality. At the same time that we show that the late behavior — convergence to a finite asymptote — of these models is almost logically immutable, we also show that the early behavior of the mortality rates can be more flexible than has been generally acknowledged. We show, in particular, that an appropriate choice of initial conditions enables one popular model to approximate any reasonable hazard-rate data. This suggests how precarious it might be to judge the appropriateness of mortality models by a perceived consilience with a favored hazard-rate function, such as the Gompertz exponential.

1. INTRODUCTION

Two mutually contradictory observations have underlain the human understanding of mortality since before there was such a thing as a theory: death is random, and death is inevitable. We are all mortal creatures, who must decay and die, but no one may know the hour or the day. And while one person is decrepit at 50 (without naming names) another is vigorous and clearheaded at twice that age.

Innumerable probabilistic models have been pressed into service to explain the randomness of aging and mortality. (This mathematical modelling runs along a distinct track from the substantial causes and effects of randomness in senescence, an extensive treatment of which may be found in [FK02].) The simplest approach, and the earliest that appeared in formal probability theory, is to represent mortality as an independent process. (See, for example, [Tod65].) Each day you receive a

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random draw from a box, with a mixture of black and white tickets. When you get a black ticket, you die. For a young and healthy person, the box may have but a single black ticket, with millions of white. Later in life the contents shift to more black. This model gives some sense of the uncertainty of death, but the aging process itself — reflected here in the changing composition of the box — is not random.

The next step is to represent aging as a markov process, that is, a process whose random future development depends only on the current state. By a “markov mortality model” we will mean a process which is “killed” at a random stopping time, according to the behavior of a markov process, which itself is typically unobserved. Both the present probability of death and the likelihood of various future fates can be read off from the condition right now, without considering how the system got here. In principle, requiring the model to be markov is no constraint at all, since the “current state” may be made arbitrarily complex, so as to include whatever memory factors influence the future. In practice, though, markov models are generally assumed to have simple state spaces, representing a “vitality” often in one dimension. It should be acknowledged from the start, then, that to let a single number encode an organism’s entire condition, everything which might influence the future development of that condition, is at best a crude abstraction.

When studying stochastic models, one hopes eventually to turn up simple mathematical systems, backed by somewhat plausible stories, which reproduce some of the salient features of observed demographic statistics related to aging — usually mortality statistics. A holy grail of this quest is the Gompertz curve: the exponential increase in mortality through a wide range of the lifespan, first observed in the 1820s by B. Gompertz [Gom25]. More recently, as demographers have become more aware that the exponential rate of increase in mortality rates tends to drop at extreme ages [OC97], the logistic Gompertz curve, represented by the hazard-rate formula

$$(1) \quad h(x) = \frac{\rho e^{\theta x}}{a + e^{\theta x}},$$

has become a more appealing goal. Both the “cascading failure” model of H. Le Bras [Bra76] and the “series-parallel” model of L. Gavrilov and N. Gavrilova ([GG91]

and [GG01]), are Markov-process models of aging which aim to generate something like the logistic Gompertz hazard rate.

A recent paper by J. Weitz and H. Fraser [WF01] proposes to explain just the plateaus in mortality rates at extreme ages, particularly those observed in flies [Vau97], by treating life as a Brownian motion with drift toward death. This is essentially the same model that J. Anderson [And00] analyzes as well. On a very general level, this does advance the discussion of mortality plateaus. Demographers have debated two classes of explanations for mortality plateaus. (References to the literature on explaining mortality plateaus may be found on page 11 of [Aus01]. Another discussion may be found in [Vau98].) On the one side are the advocates of population heterogeneity. Each individual, they say, continues the steep climb up his or her own mountain of exponentially increasing risk of death; when we look at population data, though, this clear picture is obscured by variation in the initial mortality of different individuals. At extreme ages the rapid rise in individual mortality rates is compensated by the increasingly rapid filtering out of weaker individuals. On the other side are the advocates of temporal heterogeneity. These see the aging process at extreme ages as being slowed down in essential ways — for instance, by the waning mitotic capacity of somatic cells, which retards the growth of cancerous tumors — which eventually restrain the increase in mortality rates. (A distinct explanation, described by J. Vaupel *et al.* [Vau98], and modelled by B. Charlesworth [Cha01] is termed by Vaupel “mortality correlation”. This is embedded specifically in the mutation-accumulation theory of senescence. If organisms deteriorate at advanced age because the force of selection to exclude deleterious mutations with age-specific effects declines with the age of effect, then an unceasing rise in mortality rates demands that the late-age mutations truly inflict no debility on the earlier years.)

The approach of Weitz and Fraser is rather different from all of these. Superficially, there are significant complaints one could make against their model. Their vitality has no obvious interpretation, particularly when vitalities can become arbitrarily high. The model collapses a newborn together with an individual whose vitality has returned to the starting point randomly. (This is the defect, mentioned before, of one-dimensional state-spaces.) The linear decline has little basis

(and what basis there is, surveys of biodynamic measurements such as [SM60] and [SY01], do not seem to associate death with a specific threshold). There is no obvious reason why a diffusion model should be considered appropriate — in fact, when one considers measurements of individual physical capacities, as opposed to population averages, one sees hints of significant discontinuities [Hor81].

Putting aside these cavils, though, at the core of their paper is the observation that no special pleading is required to generate mortality plateaus. This is an important point, which deserves to be rescued from the narrowness of their methods. While these authors proffer an intriguing example of mortality plateaus arising *ex nihilo*, they present no basis to judge whether this example is exceptional, or whether mortality plateaus would be a feature of more realistic models. Their computation is possible only for this one model; essentially no other model could be studied with analogous means. At the same time — and, we think, even more problematic — the methods they apply do not approach an explanation of the phenomenon. There is a computation, nothing more.

Markov models are more likely to guide our thinking along productive lines, we contend, when we step back from the particulars to the general theory. The details of the computations for one model or another, such as those carried out by Weitz and Fraser, tell us only that a given model does exhibit mortality plateaus; the reasons are buried in algebra and diagrams. When we consider the abstract theory, though, we see that mortality plateaus are a generic feature of markov mortality models, for reasons which are essentially distinct from those which have been advanced in the demographic literature.

A broad range of markov processes also settle into a constant “mortality rate” for a substantially different reason, namely, the convergence to “quasistationary distributions”. As the process progresses, the distribution of its state is being shaped by two forces: random motion, which tends to spread the mass out and shift it in certain preassigned directions; and deaths, which lop off mass at each point at a fixed rate. It turns out that there are certain distributions of probability mass whose shapes are stable, so that their levels sink equally at every location. Intuitively, this means that mass is concentrated in locations with lower mortality rates, so that the flow out will balance the slow death. What is more, it can

be shown in many cases that no matter where the process starts, if we wait long enough the distribution of those individuals who survive will be close to a certain one of these quasistationary distributions. The mortality rate, of course, will also approach the mortality rate averaged over this distribution. In other words, the mortality rate stops increasing, not because we have selected out an exceptional subset of the population, but because the condition of the survivors is reflective of their being survivors, even though they started out the same as everyone else. A population piled up in the low-vitality domain is unstable. Selection, one might say, acts on the population, not on the individuals. What is more, when the state space has regions of differing mortality rates, the surviving population will be found concentrated in the portion of lower mortality.

To suggest a banal analogy, compare this problem to the “mortality” of automobiles, such as has been described by J. Vaupel [Vau97]. It is natural to expect that a 2000 automobile will be in better condition than a 1990 automobile (barring a decline in the craft of automobile engineering), and consequently less likely to break down. This will continue for some time into the past. But will the 1970 automobile be more or less prone to breaking down than an old-timer from 1930? There are very few 1930s automobiles still in service, but those that there are seem likely to be in especially good condition. This is not because the survivors necessarily were unusually sturdy to begin with, but rather, that their survival reflects a special life course.

Some parallels might be drawn to the notion of “induced demographic schedules”, proposed by Vaupel *et al.* [Vau98] as one explanation for mortality deceleration. This refers to the ability of some organisms to switch among two or more distinct life histories, often with wide disparities in the typical lifespans. This is similar to our notion, in that the organisms may begin life identical, but become heterogeneous in the course of their lives, perhaps because of environmental influences. An important difference is that we require no specialized life-history adaptations. The heterogeneity that develops, and that induces the mortality plateaus, is in the vitality itself, not in an extraneous genetic switch. (This is not intended as an

argument against induced demographic schedules, which are certainly a real phenomenon, and which may contribute to mortality deceleration; we wish merely to point up the differences to our concept.)

In section 3 we offer an account of some general theory of quasistationary distributions. Much of this is hoary in the mathematical literature, although we do offer a few improvements. We discuss some conditions which guarantee convergence to quasistationary distributions can be guaranteed, and allow the limits to be computed. In section 4 we apply this theory to a number of examples, including those that we have already mentioned. We show there what kinds of information may be computed about quasistationary distributions, and what inferences we may draw. In particular, we see that in the constant-drift model of Weitz-Fraser and Anderson, the limit mortality is $b^2/2\sigma^2$, where b is the drift and σ the diffusion constant. The vitality converges to a gamma distribution, with shape parameter 2 and exponential rate b/σ .

In section 5 we move from the behavior as time goes to infinity, to the early behavior of some models. Researchers often exult in the hazard rates that they crank out of their models, seeing in them passable reflections of real data. Some researchers, such as L. Gavrilov and N. Gavrilova ([GG91] and [GG01]), have allowed themselves to be misled by the appearance of the Gompertz curve into accepting an erroneous computation. But even when the computation is correct, it may be rash to infer from mere consilience of theoretical and empirical curves a canonical derivation of the observed pattern. In most cases, the model presented is only one of a family of possibilities that are equally plausible, at least superficially. In particular, we show how the choice of a starting distribution provides enormous latitude to shape the mortality rates in the drifting Brownian motion model.

2. FINITE STATE SPACES

2.1. An introductory example. Consider a model in which an organism has two possible states: healthy and sick. Healthy individuals may stay healthy or get sick; sick individuals may stay sick or get healthy, but they may also die. For definiteness, let us say that the rate of healthy individuals getting sick is 1, the rate of sick individuals getting well is 2, and their rate of dying is 1. A Markov process is represented by a matrix Q with entries q_{ij} , being the rate at which a

process currently in state i makes jumps to the state j . The sum $\sum_j q_{ij}$ of the transition rates in any given row is 1. The unkilld process described above has matrix $\begin{pmatrix} -1 & 1 \\ 2 & -2 \end{pmatrix}$, which means that it converges to a stationary state (corresponding to the left eigenvector with eigenvalue 0) in which 2/3 are healthy and 1/3 sick.

Naively, one might then expect that the limiting mortality rate would be 1/3. In fact, though, it will be smaller, because an individual who has survived a very long time is more likely to be healthy than an average individual. To compute this, we take the infinitesimal matrix of the killed markov process. We can either define a third ‘‘cemetery’’ state ∂ , such that transitions to ∂ are equivalent to dying. Then we get the 3×3 transition matrix

$$(2) \quad Q = \begin{pmatrix} -1 & 1 & 0 \\ 2 & -3 & 1 \\ 0 & 0 & 0 \end{pmatrix}.$$

Equivalently, we can just drop the last row and column, and work with the *sub-markov* transition matrix

$$(3) \quad Q = \begin{pmatrix} -1 & 1 \\ 2 & -3 \end{pmatrix}.$$

This has two eigenvalues, $-.268$ and -3.73 . The larger one, $-.268$, will be the limiting mortality rate. To make this explicit, we know that if the starting distribution is (p_h, p_s) , then the distribution at time t will be $(p_h, p_s) \exp(tQ)$. We have (by diagonalizing Q)

$$\exp(tQ) = \begin{pmatrix} .789e^{-.268t} + .211e^{-3.73t} & .289e^{-.268t} - .289e^{-3.73t} \\ .577e^{-.268t} - .577e^{-3.73t} & .211e^{-.268t} + .789e^{-3.73t} \end{pmatrix}.$$

Thus

$$\begin{aligned} e^{.268t} (P^t\{\text{healthy}\}, P^t\{\text{sick}\}) \\ = (.789p_h + .577p_s, .289p_h + .211p_s) + e^{-3.46t} (.211p_h - .577p_s, -.289p_h + .789p_s). \end{aligned}$$

For a healthy individual, we start with $p_h = 1$ and $p_s = 0$:

$$P\{\text{survive until time } t\} = P^t\{\text{healthy}\} + P^t\{\text{sick}\} = 1.078e^{-.268t} - 0.078e^{-3.73t}.$$

The conditional probability of survival is then

$$\begin{aligned} & \mathbb{P}\{\text{survive until time } t + s \mid \text{survive until time } t\} \\ &= \frac{e^{-.268s} - 0.072e^{-3.46t-3.73s}}{1 - 0.072e^{-3.46t}} \xrightarrow{t \rightarrow \infty} e^{-.268s}. \end{aligned}$$

Note, as well, that conditioned on survival until t , as $t \rightarrow \infty$ the probability of being healthy converges to

$$\frac{.789p_h + .577p_s}{1.078p_h + .788p_s} = .732,$$

independent of the starting state. This distribution of healthy and sick — which is the same as the top eigenvector — is what we call the quasistationary distribution.

2.2. General theory for finite state spaces. As in the above example, we may represent death as entrance into the cemetery state ∂ . A markov process with a single absorbing state will be referred to as a *killed markov process*. We will follow the alternative route of dropping the cemetery state, and allowing the particle simply to disappear at death. This turns the markov process (where the sum of the probabilities among the possible states is always 1) into a submarkov process (where the sum of the probabilities is decreasing with time).

Suppose we have a submarkov process, whose state space is a finite set \mathcal{X} . We write the infinitesimal rate of transition from state i to state j as q_{ij} . The rate of leaving state i is q_{ii} , so it is equal to $-k_i - \sum_{j \neq i} q_{ij}$, where k_i is the rate of dying at state i . We say that a state y is *accessible* from the state x if there is a sequence of states $x = i_0, i_1, \dots, i_k = y$ such that $q_{i_m i_{m+1}} > 0$ for every m . Stated simply, this means that if the process starts at x , it has a nonzero probability of arriving eventually at y . The process is said to be *irreducible* if every state is accessible from every other.

Let \mathcal{A} be the set of states which are accessible from all other states. Suppose that \mathcal{A} is nonempty. Let T be the time of “death”, and let $T_{\mathcal{A}}$ be the first time the process arrives in \mathcal{A} . Conditioned on $T > t$, the probability of $T_{\mathcal{A}} > t$ (that is, the probability that the process has never been in \mathcal{A} up to time t) goes exponentially to 0. Note that \mathcal{A} is an absorbing set. Thus, conditioned on survival up to time t , the process becomes concentrated on \mathcal{A} .

Proposition 1. *Let λ be the eigenvalue of $-Q$ with the smallest real part. Then λ is purely real and nonnegative, and is a simple eigenvalue. The unique left eigenvector π with $\sum \pi_i = 1$, and right eigenvector v with $\sum \pi_i v_i = 1$, corresponding to λ , are nonnegative, and all components in A are positive. For any states i and j ,*

$$\lim_{t \rightarrow \infty} P_i\{X_t = j \mid T > t\} = \pi_j$$

and

$$\lim_{t \rightarrow \infty} P\{T > t + s \mid T > t\} = e^{-\lambda s}.$$

(The i in the subscript represents the starting state.) In addition, for any states i and j ,

$$\lim_{t \rightarrow \infty} e^{\lambda t} P\{X_t = i \mid X_0 = j\} = v_j \pi_i.$$

Proof. The positivity results are simply the Perron-Frobenius Theorem [HJ85], applied to e^{tQ} for arbitrary positive t . The rest is elementary linear algebra. The theory of such ‘‘Perron-Frobenius eigenvalues’’ is discussed at length in [Sen73]. \square

Note that when the set A is empty, the state space may be decomposed into subsets which are mutually inaccessible. The above result may then be applied to the subsets separately.

A version of this theory for finite state spaces and discrete time was worked out in [DS65], and extended to some cases of infinite discrete state spaces in [SVJ66]. Infinite state spaces are not so easy to treat in a comprehensive framework, but some general results for the special case of birth-death processes may be found in [Doo91].

3. QUASISTATIONARY DISTRIBUTIONS FOR GENERAL STATE SPACES

A general fact about killed markov processes, under fairly general conditions, is that their rates of killing, averaged over a long time, converge to a finite rate, called the *decay parameter*. The major results in section 3.1 are all due to R. Tweedie and several coauthors. In the greatest generality, the existence of a decay parameter λ is a fairly weak statement. It states, essentially, that $P_t(x, A)$ (the probability that the process started from x will be in the set A at time t) declines, on an exponential scale, at a rate on the order of $e^{-\lambda t}$. The decay parameter is defined by the existence of so-called subinvariant measures and functions, a generalization

of eigenmeasures and eigenfunctions. The exact statement is given in Proposition 3.

We will say that the decay parameter is the *asymptotic killing rate* for the process — a much stronger statement, and one that is closer to our concerns — if the killing time for the process started at any point x satisfies

$$(4) \quad \lim_{t \rightarrow \infty} \mathbb{P}_x \{T > t + s \mid T > t\} = e^{-\lambda s}.$$

Clearly, if for each $x \in \mathcal{X}$ there is a positive constant c_x such that

$$\lim_{t \rightarrow \infty} e^{\lambda t} \mathbb{P}_x \{T > t\} = c_x,$$

then λ is the asymptotic killing rate. As we explain below, a sufficient condition for the decay parameter to be the asymptotic killing rate is that the process have a property called λ -positivity. A characterization of λ -positive processes in terms of subinvariant measures and functions, due to Tweedie and P. Tuominen, is given here as Proposition 4.

Even when the process is not λ -positive, so that the rate of decay is not precisely exponential, we may still have an asymptotic killing rate if the conditional probability converges to a quasistationary distribution. That is,

$$\lim_{t \rightarrow \infty} \mathbb{P}_x \{X_t \in A \mid T > t\} = \mu(A),$$

where μ satisfies equation (9) for $\ell = \lambda$, with the inequality replaced by equality. This follows because

$$\begin{aligned} \lim_{t \rightarrow \infty} \mathbb{P}_x \{T > t + s \mid T > t\} &= \lim_{t \rightarrow \infty} \frac{\int_{\mathcal{X}} \mathbb{P}^t(x, dy) P^s(y, \mathcal{X})}{\int_{\mathcal{X}} \mathbb{P}^t(x, dy)} \\ &= \int_{\mathcal{X}} P^s(y, \mathcal{X}) \mu(dy) \\ &\leq e^{-\lambda s}. \end{aligned}$$

It is this criterion that we will use in section 3.2 for diffusions on an unbounded interval.

While these theorems provide a useful overview of the convergence properties of submarkov processes, they are limited in two ways. On the one hand, the conditions are difficult to check in general. In particular, finding subinvariant measures and functions (and, which is essential, knowing that we have found all of them) is

rarely possible in infinite state spaces, except when the state-space is the real line, where we have the machinery of ordinary differential equations to hand. On the other hand, the conditions are too strict. When the process is not λ -positive, the general theory tells us very little. Many of the models that would interest us — in particular, diffusions which are not confined to a compact set — are not λ -positive. They may, nonetheless, have asymptotic killing rates. The reason is straightforward: when the process is λ -positive, the decay is exactly exponential. But in processes such as the diffusion models we examine in sections 4.1 and 4.3, the probability of survival up to time t falls as $\frac{1}{t}e^{-\lambda t}$. (In technical terms, this happens because the generator has a continuous spectrum, rather than the discrete spectrum which characterizes diffusions on compact intervals.) This rules out an application of positivity methods, but has no effect on the results that we are concerned with, which refer only to relative probabilities: the probability of being in a given set conditioned on having survived for a very long time. In section 3.2 we derive a general result for the long-term behavior of one-dimensional diffusion processes. In section 3.3 we explain why killed Brownian motions in general dimensions are indeed λ -positive, as long as they are confined to a compact set.

3.1. General theory. The general statements of this section require a fair amount of technical terminology from the theory of markov processes. These results will not be applied directly in the sequel, and may be skipped without significantly impairing understanding. Some of the terminology will reappear in the proofs of section 3.2.

The most naive representation of a markov process is its *transition semigroup*, by which we mean a collection of measures $P_t(x, A)$, representing the probability of finding the process in the measurable set A at time $t + s$, given that it was at x at time t . For each t and x , $P_t(x, \mathcal{X}) \leq 1$. If this probability of the process being anywhere in \mathcal{X} is identically equal to 1, the process (and the kernel) are called *markov*; otherwise, it is *submarkov*. The difference may be thought of as the probability that the process has “died”. By convention, we transform a submarkov process into a markov process by adjoining an absorbing state ∂ , and defining the semigroup on the extended state space $\mathcal{X} \cup \{\partial\}$ by $P_t(x, \{\partial\}) = 1 - P_t(x, \mathcal{X})$.

Conversely, starting from a markov process with measurable paths, we can define a submarkov process by “killing”. A *killing rate* is a measurable function $\kappa : \mathcal{X} \rightarrow [0, \infty]$. The killed process \tilde{X}_t is defined by adjoining to the probability space an exponential random variable \tilde{T} with unit rate. We then define a “killing time” T as the solution to

$$\int_0^T \kappa(X_t) dt = \tilde{T},$$

so that conditioned on the process surviving to time t , the probability of killing in the next infinitesimal instant of time dt is $\kappa(X_t)dt$. We set

$$(5) \quad \tilde{P}^t(x, A) = P_x\{X_t \in A \text{ and } T > t\}$$

The killed markov process is defined by

$$\tilde{X}_t = \begin{cases} X_t & \text{if } t < T, \\ \partial & \text{if } t \geq T. \end{cases}$$

In some cases a submarkov process may be defined by an *infinitesimal generator* \mathcal{L} , which satisfies

$$(6) \quad \mathcal{L}f = \left. \frac{d}{dt} P^t f \right|_{t=0}.$$

for a sufficiently rich class of functions $f : \mathcal{X} \rightarrow \mathbb{R}$. There is a formal adjoint \mathcal{L}^* , which satisfies

$$(7) \quad \mathcal{L}^* P^t(x, \cdot) = \frac{d}{dt} P_t(x, \cdot).$$

For more details about generators, see a text on markov processes, such as [RY90].

The notion of irreducibility becomes more involved than in finite state spaces. A submarkov process on a finite or countable state space is irreducible when, given any two states i and j , there is a nonzero probability that when the process is started at i , it will eventually reach j . In a larger state space, the probability of hitting an individual point is typically 0. Instead we speak of the process eventually spending time in certain sets, identified as having nonzero measure according to some measure ϕ . The transition semigroup P^t is said to be ϕ -irreducible if there is a nonzero σ -finite measure ϕ on \mathcal{X} such that for every $x \in \mathcal{X}$ and measurable A with $\phi(A) > 0$,

$$(8) \quad \int_0^\infty P^t(x, A) dt > 0.$$

For any real number ℓ , the σ -finite measure μ on \mathcal{X} is said to be ℓ -subinvariant for P_t if for all t and all measurable A with $\mu(A)$ finite,

$$(9) \quad P^t \mu(A) := \int_{\mathcal{X}} P^t(x, A) d\mu(x) \leq e^{-\ell t} \mu(A);$$

if the inequality (9) is an equality, then we call μ ℓ -invariant. If f is a function from \mathcal{X} to \mathbb{R}^+ , it is said to be ℓ -subinvariant for P_t if for all t

$$(10) \quad P^t f(x) := \int_{\mathcal{X}} P^t(x, dy) f(y) \leq e^{-\ell t} f(x),$$

except for at most an exceptional set of points x with ϕ -measure 0. Except for some technical details, which we will not discuss here, an ℓ -invariant function (or measure) is the same as an eigenfunction (or eigenmeasure) of the generator (or its adjoint) with eigenvalue $-\ell$. In the case of diffusions, the generator is a differential operator, allowing the problem to be subsumed into the theory of differential equations. This case will be discussed in sections 3.2 and 3.3.

There is a powerful, though almost trivial, relationship between invariant measures and decay rates.

Proposition 2. *Let μ be the starting distribution for the submarkov process X_t . If there exists a λ -subinvariant measure ν such that $C := \sup_{x \in \mathcal{X}} d\mu/d\nu(x)$ is finite, then*

$$(11) \quad \mathbb{P}\{\text{survive until time } t\} \leq C e^{-\lambda t},$$

which gives a lower bound on the decay parameter. If there exists a λ -superinvariant measure ν such that $c := \inf_{x \in \mathcal{X}} d\mu/d\nu(x) > 0$, then

$$(12) \quad \mathbb{P}\{\text{survive until time } t\} \geq c e^{-\lambda t},$$

which gives an upper bound on the decay parameter. If there exists a λ -invariant measure ν such that $\infty > C \geq c > 0$, then

$$(13) \quad C e^{-\lambda t} \geq \mathbb{P}\{\text{survive until time } t\} \geq c e^{-\lambda t},$$

which implies that the decay parameter exists, and is equal to λ .

Proof. We prove statement (11). The other proofs are essentially the same. The probability of survival is given by

$$\int_{\mathcal{X}} P^t(x, \mathcal{X}) \mu(dx) \leq C \int_{\mathcal{X}} P^t(x, \mathcal{X}) \nu(dx) \leq C e^{-\lambda t} \nu(\mathcal{X}) = C e^{-\lambda t}.$$

□

This result is useful, in that it allows us to derive bounds on the decay rate in particular cases. The upper bound on the decay parameter holds, loosely speaking, if the starting condition is sufficiently diffuse (not concentrated at points, in particular) and if it avoids overemphasizing the boundary (when the invariant measure is forced to 0 there). The lower bound holds, more or less, when the starting measure is sufficiently spread out: putting positive weight wherever the invariant measure does. Of course, we may start with a point mass and let the process run for a short time, until the distribution has spread out, and then treat what results as the new starting distribution.

Intuitively, one would expect that if the process is sufficiently smooth, and the state space is compact, then it should be possible to compare the top invariant measure with the result of running the process for a fixed time, and so apply equation (13). For diffusions on a bounded domain in \mathbb{R}^n with Hölder differentiable coefficients, this is shown in [GQZ88].

It would help to know, more generally, when such sub- and super-invariant measures exist. In addition, we might like to know whether the average decay rate holds uniformly over all starting measures. The most important results along these lines are due to R. Tweedie and various coauthors. We summarize some of this work in the following Theorem, extracted from more extensive results in Theorems 2, 3, and 6 of [TT79], and Proposition 3.1 of [Twe74].

Theorem 3 (Tuominen and Tweedie). *Let P^t be a ϕ -irreducible, submarkov transition semigroup, such that $P^t(x, A)$ is continuous in t for each x and measurable A . Let λ be the supremum of those ℓ such that there is an ℓ -subinvariant measure for P^t . Then there exists a λ -subinvariant function f and a λ -subinvariant measure π . There is a ϕ -null set N , such that if A is a measurable set with $0 < \pi(A) < \infty$ and $x \notin N$, then*

$$(14) \quad \int_0^\infty e^{st} P^t(x, A) dt < \infty \text{ if } s < \lambda, \text{ and} \\ \int_0^\infty e^{st} P^t(x, A) dt = \infty \text{ if } s > \lambda.$$

If, in addition, $\inf_{x \in A} f(x) > 0$, then for $x \notin N$,

$$(15) \quad \lim_{t \rightarrow \infty} \frac{1}{t} \log P^t(x, A) = -\lambda.$$

We say that the semigroup P^t is λ -transient if

$$\int_0^\infty e^{\lambda t} P^t(x, A) dt$$

is finite for all $x \in \mathcal{X}$ and all A with $\phi(A) > 0$. Otherwise, P^t is said to be λ -recurrent. Theorem 3 of [TT79] tells us that when P^t is recurrent, there is a unique λ -subinvariant measure π and a unique λ -subinvariant function f , and these are λ -invariant. If $\int f d\pi$ is finite, then we say that P^t is *positive λ -recurrent* (or *λ -positive*).

Conversely, we have (combining Theorems 4 and 5 of [TT79] with Proposition 4.4 of [Twe74])

Proposition 4. *Let P^t be a ϕ -irreducible submarkov semigroup such that $P^t(x, A)$ is a continuous function of t for every x and A . If for some ℓ there exists an ℓ -invariant function f and a ℓ -invariant measure π , such that $\int f d\pi$ is finite, then $\ell = \lambda$ and the process is λ -positive.*

For a λ -positive process,

$$(16) \quad \lim_{t \rightarrow \infty} e^{\lambda t} P^t(x, A) = \frac{f(x)\pi(A)}{\int f d\pi}$$

for π -almost every x , and every measurable A such that $\inf_{x \in A} f(x) > 0$. The asymptotic killing rate is λ .

3.2. One-dimensional diffusions with killing. A markov process with continuous sample pathson some subset of \mathbb{R}^d is called a *diffusion*. Most reasonable one-dimensional diffusions that appear in practice may be defined, for state space $\mathcal{X} = (r_1, r_2)$, where r_1 may be $-\infty$ and r_2 may be $+\infty$, by three functions: $\sigma : \mathcal{X} \rightarrow [0, \infty)$, $b : \mathcal{X} \rightarrow \mathbb{R}$, and $\kappa : \mathcal{X} \rightarrow [0, \infty)$. The function b , called the drift, is the instantaneous rate of motion of the process:

$$b(x) = \lim_{\Delta t \rightarrow 0^+} \frac{1}{\Delta t} E[X_{t+\Delta t} - x \mid X_t = x].$$

The drift will be assumed continuously differentiable. The function σ , called the diffusion rate, will be assumed twice continuously differentiable and nonzero on the

interior of \mathcal{X} . It has the value

$$\sigma^2(x) = \lim_{\Delta t \rightarrow 0^+} \frac{1}{\Delta t} \mathbb{E}[(X_{t+\Delta t} - x)^2 | X_t = x].$$

The instantaneous rate of killing is κ , and functions according to the general recipe of section 3.1. The motion (without killing) satisfies the stochastic differential equation

$$(17) \quad dX_t = \sigma(X_t)dW_t + b(X_t)dt,$$

where W_t represents a standard Brownian motion. The infinitesimal generator of the unkilld process is (see, for example, section VII.2 of [RY90])

$$(18) \quad \mathcal{L}\phi(x) := \lim_{t \downarrow 0} \frac{E_x[\phi(X_t)] - \phi(x)}{t} = \frac{1}{2}\sigma^2(x)\phi''(x) + b(x)\phi'(x),$$

and the adjoint operator is

$$(19) \quad \mathcal{L}^*\phi = \frac{1}{2}(\sigma^2(x)\phi(x))'' - (b(x)\phi(x))'.$$

The generator describes the behavior of the diffusion in the interior of \mathcal{X} . To describe the complete behavior of the diffusion we need to add boundary conditions (as discussed below), to determine whether it is reflected or killed at the endpoints. By the Feynman-Kac formula (Proposition VIII.3.10 of [RY90]), the infinitesimal generator of the process with killing is $\mathcal{L} - \kappa$.

We may simplify the problem somewhat by assuming that σ is identically 1. There is no loss of generality since (following [Fel52]) we can replace X_t by $Y_t = F(X_t)$, where $F(x) := \int_{x_0}^x du/\sigma(u)$, where c is an arbitrary point in (r_1, r_2) . The killing rate for Y_t becomes $\kappa(F^{-1}(Y_t))$, while the drift may be computed by Itô's formula to be

$$(20) \quad \frac{b(F^{-1}(Y_t))}{\sigma(F^{-1}(Y_t))} - \sigma'(F^{-1}(Y_t)).$$

Since σ is positive on the interior of the interval, this transformation is finite. From now on, we will always assume, unless otherwise stated, that the diffusion rates of our one-dimensional diffusions are identically 1.

The endpoints of the interval may be classified into four types: natural boundaries, regular boundaries, entrance boundaries, and exit boundaries. A *natural boundary* is a boundary which the process will never reach, and from which the process cannot be started. An example is $\pm\infty$ as “endpoints” for simple Brownian

motion on the real line. Natural boundaries must be infinite. A *regular boundary* is a boundary which the process can reach in finite time, and from which it could be started. Examples are the endpoints 0 and 1 for reflected Brownian motion on the unit interval. Regular boundaries must be finite. They may be reflecting, absorbing (meaning that the process is killed when it hits), or partially reflecting (meaning that the process is “sometimes” reflected and “sometimes” killed when it hits — this is a vague description of a technically somewhat involved construction). An *entrance boundary* is a boundary that the process can start from, but which it cannot reach in finite time from anywhere else. An example is the endpoint 0 for the Bessel process of nonnegative order, which we discuss in section 4.4. Finally, an *exit boundary* is an endpoint that the process can reach in finite time, but which cannot be the starting point of the process. An example is the boundary $+\infty$ for the process X_t defined by the SDE

$$dX_t = dW_t + X_t^2 dt.$$

(Observe that the process without the stochastic term runs from 1 to ∞ in 1 unit of time, and the finite stochastic term will only change the timing.) Entrance and exit boundaries may be finite or infinite. Exit boundaries are problematic, for our present purposes, because the process almost surely runs off to them in bounded time. We will assume that the processes we consider do not have exit boundaries. Entrance and natural boundaries are jointly referred to as *inaccessible boundaries*.

It is straightforward to classify the boundaries on the basis of the drift and diffusion functions. Fix any point x_0 in the interior of the interval (r_1, r_2) , and define

$$B(x) = \int_{x_0}^x 2b(z) dz.$$

(If we do not make the simplifying assumption $\sigma = 1$, then $b(z)$ must be replaced in this definition by $b(z)/\sigma^2(z)$.) The integral

$$p(x) = \int_{x_0}^x e^{-B(s)} ds$$

is known as the *scale function* of the diffusion. (The choice of x_0 only affects it by adding an irrelevant constant.)

The boundary r_i is regular if

$$(21) \quad \int_{x_0}^{r_i} e^{-B(x)} dx < \infty \quad \text{and} \quad \int_{x_0}^{r_i} e^{B(x)} dx < \infty.$$

If the boundary r_i is not regular, it is an exit boundary if

$$(22) \quad \int_{x_0}^{r_i} e^{-B(x)} \int_{x_0}^x e^{B(y)} dy dx < \infty.$$

If the boundary r_i is not regular, it is an entrance boundary if

$$(23) \quad \int_{x_0}^{r_i} e^{B(x)} \int_{x_0}^x e^{-B(y)} dy dx < \infty.$$

The boundary r_i is a natural boundary in all other circumstances, which is to say that

$$(24) \quad \int_{x_0}^{r_i} e^{-B(x)} \int_{x_0}^x e^{B(y)} dy dx = \infty \quad \text{and} \quad \int_{x_0}^{r_i} e^{B(x)} \int_{x_0}^x e^{-B(y)} dy dx = \infty.$$

At a regular boundary, the functions ϕ to which the generator is applied are assumed to satisfy a boundary condition of the form

$$(25) \quad (1-p)e^{-B(r_i)}\phi = p(\phi' - b\phi)$$

at the endpoints, where $0 \leq p \leq 1$. At an endpoint where $p = 0$, the process is instantaneously killed; where $p = 1$, the process is reflected; and for intermediate values, the process is killed at a rate $p/(1-p)$ relative to the local time it spends at that endpoint. (The form of the boundary condition for a regular boundary is given as (19.17) in [Fel52].)

We define the function $\phi_\lambda : \mathcal{X} \rightarrow \mathbb{R}$ to be the unique nonzero solution to the initial value problem

$$(26) \quad \frac{1}{2} \frac{d^2}{dx^2} \phi_\lambda - \frac{d}{dx} (b \cdot \phi_\lambda) - \kappa \phi_\lambda = -\lambda \phi_\lambda$$

with $(1-p_i)e^{-B(r_i)}\phi_\lambda(r_i) = p_i(\phi'_\lambda(r_i) - b(r_i)\phi_\lambda(r_i))$,

if it exists. Here p_i represents the degree of reflection at the boundary point r_i . It is implicitly 0 at an inaccessible boundary.

Theorem 5. *Suppose that r_1 and r_2 are both regular boundaries. Let $\underline{\lambda} = \min\{\lambda : \phi_\lambda \text{ exists}\}$. Suppose*

$$(27) \quad \phi_{\underline{\lambda}} \text{ is nonnegative.}$$

If both boundaries are reflecting and $\kappa = 0$ almost everywhere then $\underline{\lambda} = 0$; otherwise, $\underline{\lambda}$ is positive. For any measurable subset $A \subset (r_1, r_2)$, and any starting point x ,

$$(28) \quad \lim_{t \rightarrow \infty} e^{\lambda t} P_x \{X_t \in A\} = \frac{e^{-B(x)} \phi_{\underline{\lambda}}(x) \cdot \int_A \phi_{\underline{\lambda}}(y) dy}{\int_{r_1}^{r_2} e^{-B(y)} \phi_{\underline{\lambda}}^2(y) dy}.$$

The asymptotic killing rate is $\underline{\lambda}$.

If b is finite at both boundaries then condition (27) is automatically satisfied.

Proofs of all the results in this section may be found in [SE].

Note that the orthogonality of eigenfunctions implies that $\underline{\lambda}$ is the only eigenvalue for which the boundary value problem (26) has a nonnegative solution.

Theorem 6. *Suppose that r_1 is a regular boundary, the drift b is continuous at r_1 and $r_2 = \infty$ a natural or entrance boundary, and that $\int_{r_1}^{\infty} e^{B(z)} dz < \infty$. (An equivalent result holds if r_2 is the regular boundary and r_1 the natural boundary.) Suppose, too, that*

$$(29) \quad \int_{r_1}^{\infty} e^{B(z)} dz < \infty,$$

and

$$(30) \quad \liminf_{z \rightarrow \infty} z^{-2} (b(z)^2 + b'(z) + 2\kappa(z)) > -\infty.$$

Then $\underline{\lambda}$ is finite, and is equal to the decay parameter for the process X_t . For any measurable subset $A \subset [r_1, \infty)$,

$$(31) \quad \lim_{t \rightarrow \infty} P \{X_t \in A \mid T > t\} = \frac{\int_A \phi_{\underline{\lambda}}(z) dz}{\int_{r_1}^{\infty} \phi_{\underline{\lambda}}(z) dz},$$

and $\int_{r_1}^{\infty} \phi_{\underline{\lambda}}(z) dz$ is finite. The asymptotic killing rate is $\underline{\lambda}$.

Note that the condition (30) is fairly weak: it is automatically satisfied if the drift $b(z)$ does not drop suddenly for large z . There is little cost in imposing this condition, since it constrains only the local fluctuations of the drift. The condition (29), on the other hand, is a global constraint on the behavior of $b(z)$ as $z \rightarrow \infty$. Essentially, this requires the drift to be sufficiently negative to keep the mass from drifting off to ∞ . This is clearly too restrictive, since in some models (such as the one discussed in section 4.3) the process is prevented from drifting off to ∞ not by a countervailing drift, but by an increasing killing rate, which forces the conditioned process to lurk near the origin. For such models, we have the following result:

Theorem 7. *The conclusions of Theorem 6 remain valid when the condition (29) is replaced by*

$$(32) \quad \liminf_{z \rightarrow \infty} \kappa(z) > \underline{\lambda}.$$

3.3. Killed Brownian motion on a compact set. Let \mathcal{X} be a bounded open subset of \mathbb{R}^n , with a smooth boundary. Let $\kappa : \mathcal{X} \rightarrow \mathbb{R}^+$ be a measurable function, and let \mathcal{L} be the generator of a diffusion, whose diffusion rate is differentiable and whose drift is continuous on a neighborhood of \mathcal{X} . The diffusion rate for a process in \mathbb{R}^n is a differentiable function on \mathcal{X} , whose values are $n \times n$ matrices. The drift is a continuous function that takes values in \mathbb{R}^n . For any distribution μ on \mathcal{X} we may define a process X_t which starts at μ , and continues as a diffusion with generator \mathcal{L} until the time T , which is the minimum of the killing time defined by κ and the first time when the process hits the boundary of \mathcal{X} .

In general, we have the following theorem due to M. Donsker and S. Varadhan [DV76, Theorem 2.2]:

Theorem 8 (Donsker and Varadhan).

$$(33) \quad \lim_{t \rightarrow \infty} \sup_{x \in \mathcal{X}} \log P_x \{T > t\} = \sup_{\mu} \inf_{\phi} \int_{\mathcal{X}} \frac{\mathcal{L}\phi(z) - \kappa(z)\phi(z)}{\phi(z)} d\mu(z),$$

where μ ranges over all probability measures on the closure of \mathcal{X} , and ϕ ranges over the functions in the domain of \mathcal{L} which are bounded away from 0.

R. Pinsky [Pin85] has cited this theorem in a stronger form, with the supremum over $x \in \mathcal{X}$ on the left-hand side removed (so that the result applies to the decay parameter from any starting point). It is not clear to us how the stronger form follows from the weaker, in general.

If the base diffusion is Brownian motion — that is, with no drift, and with σ everywhere equal to the identity matrix — we may apply the same arguments as for Theorem 5 to show

Theorem 9. *Let X_t be Brownian motion on the bounded domain \mathcal{X} in \mathbb{R}^n , killed at rate κ . The process X_t is λ -positive. Let $\underline{\lambda}$ be the maximum λ such that there is a nontrivial $\phi_{\lambda} : \text{Int}(\mathcal{X}) \rightarrow \mathbb{R}^+$ satisfying*

$$(34) \quad \frac{1}{2} \Delta \phi_{\lambda} - \kappa \phi_{\lambda} = -\lambda \phi_{\lambda},$$

which converges to 0 on the boundary. (Here Δ is the Laplacian operator.) Then $\underline{\lambda}$ is the decay parameter for X_t , and the asymptotic killing rate is $\underline{\lambda}$. In addition, for any measurable set $A \subset \mathcal{X}$,

$$(35) \quad \lim_{t \rightarrow \infty} P_\mu \{X_t \in A \mid T > t\} = \frac{\int_A \phi_{\underline{\lambda}}(z) d^n z}{\int_{\mathcal{X}} \phi_{\underline{\lambda}}(z) d^n z}$$

where T is the killing time, and

$$(36) \quad \lim_{t \rightarrow \infty} P_x \{T > t + s \mid T > t\} = e^{-\underline{\lambda}s}.$$

Furthermore,

$$\lim_{t \rightarrow \infty} e^{\underline{\lambda}t} P_x \{X_t \in A\} = \frac{\int_A \phi_{\underline{\lambda}}(z) d^n z \cdot \int_{\mathcal{X}} \phi(z) d\mu(z)}{\int_{\mathcal{X}} \phi_{\underline{\lambda}}(z)^2 d^n z}.$$

More generally, as pointed out in the appendix to [Pin85], the same methods apply if $\sigma^{-1}b$ is a gradient function.

4. EXAMPLES

4.1. Constant drift and killing at 0. In the case when b is a negative constant, $\kappa \equiv 0$ on \mathbb{R}^+ , and 0 is an absorbing boundary, Theorem 6 becomes particularly easy to apply. For $\lambda \neq b^2/2$ we get the solution

$$\phi_\lambda(x) = \frac{1}{2\sqrt{b^2 - 2\lambda}} \left[\exp \left\{ \left(b + \sqrt{b^2 - 2\lambda} \right) x \right\} - \exp \left\{ \left(b - \sqrt{b^2 - 2\lambda} \right) x \right\} \right],$$

which changes sign for $\lambda > b^2/2$. Thus the limit mortality rate is $b^2/2$, and the density of the fitnesses of the survivors converges to

$$\phi_{b^2/2}(x) = x e^{bx},$$

which is a gamma distribution with exponential rate $|b|$ and shape parameter 2. If σ is not 1, we simply need to replace b by b/σ . (Remember that σ is constant here.)

4.2. General killing: a discrete-space example. The well-known ‘‘cascading failure’’ model was introduced by H. Le Bras [Bra76], and further studied by L. Gavrilov and N. Gavrilova [GG91]. This represents senescence as a discrete variable, with motion only in the increasing direction by steps of size 1. The rate of jumps from state x to $x + 1$ is a constant λ times x , and the process is killed at rate μx when it is in state x . One diffusion analogue of this would have a Brownian component of intensity σx when the process is at x , upward drift of magnitude bx , and killing rate $\kappa(x) = \mu x$. We will discuss this variant in section 4.3.

The concept of quasistationary distribution is still relevant to this model, even though it progresses always in the same direction, hence is not irreducible. Conditioned on survival, the process will indeed converge to a fixed quasistationary distribution, from any starting state. The difference from the standard setting is, that the distribution will depend on the starting state. We can analyze the model as follows: Assume first that X_0 is 1. Let $p = \mu/(\mu + \lambda)$ and $\alpha = \mu + \lambda$. If the particle is at state x , the probability that it dies before moving on to $x + 1$ is p . Thus, the final senescence state X_ω of the particle has geometric distribution with ratio $q = 1 - p$. Conditioned on $X_\omega = k$, the time of death T may be represented as $T = \tau_1 + \tau_2 + \dots + \tau_k$, where τ_i is exponentially distributed with parameter $i\alpha$, and all are independent. We have then

$$\mathbb{P}\{T > t \mid X_\omega = k\} = 1 - \{1 - e^{-\alpha t}\}^k.$$

(To see this, observe that the sum of exponential variables with parameters $1, \dots, k$ has the same distribution as the maximum of k exponential variables with parameter 1.) This yields

$$\mathbb{P}\{T > t\} = 1 - \sum_{k=1}^{\infty} pq^{k-1} (1 - e^{-\alpha t})^k = \frac{1}{q + pe^{\alpha t}} = \frac{\mu + \lambda}{\lambda + \mu e^{(\mu + \lambda)t}}.$$

The hazard rate is then

$$\frac{\mu(\mu + \lambda)e^{(\mu + \lambda)t}}{\lambda + \mu e^{(\mu + \lambda)t}}.$$

The rate is approximately exponential early on, and converges to $\mu + \lambda$ as $t \rightarrow \infty$. (That the rate begins as an exponential is hardly surprising. If we remove all randomness from the motion, and simply have it remain at site x for a deterministic time $1/\lambda x$, the position at time t will be approximately a constant times $e^{\lambda t}$. The hazard rate at time t will be μ times the position.)

Suppose, now, we know that an individual has survived to time t , where t is very large. What is the distribution of the individual's senescence state? It is important to notice that this is not the same as the distribution of X_t if killing were eliminated. Conditioned on survival to time t , X_t will be smaller than it would be without killing, since survival is more likely lower down. Let T_k be the

time when X_t leaves state k (or ∞ if it never reaches k). Then

$$\begin{aligned} \mathbb{P}\{X_t = k \mid T > t\} &= \frac{\mathbb{P}\{T_{k-1} < t < T_k \text{ and } X_\omega \geq k\}}{\mathbb{P}\{T > t\}} \\ &= \left((1 - e^{-\alpha t})^{k-1} - (1 - e^{-\alpha t})^k \right) q^{k-1} (q + pe^{\alpha t}). \end{aligned}$$

The distribution of X_t conditioned on survival is geometric with parameter $q(1 - e^{-\alpha t})$. As t goes to infinity, this settles into a quasistationary distribution which is geometric with parameter q : coincidentally, the same as the distribution of the state at death, X_ω .

For a general starting distribution, the limit distribution is simply the same as for $X_0 = 1$, conditioned on being no smaller than X_0 . This is

$$(37) \quad \mathbb{P}\{X_t = k \mid T > t\} = \mathbb{E}[pq^{k-X_0} \mathbf{1}_{X_0 \leq k}] = pq^k \sum_{j=1}^k q^{-j} \mathbb{P}\{X_0 = j\}.$$

4.3. A continuous version of Le Bras' process. The defining feature of Le Bras' model is that the rate of the random motion, as well as the killing rate, increase linearly with the state. We keep these features, but allow the process to move up and down, in order to arrive at a continuous process (which must be a diffusion).

We define a process on $[1, \infty)$ by the stochastic differential equation

$$(38) \quad dX_t = \sigma X_t dW_t + bX_t dt,$$

where σ is a positive constant and b is a constant larger than $\sigma^2/2$. The process starts at $X_0 = 1$, is killed at the rate kX_t , and is reflected when it hits 1. By Ito's formula we see that X_t evolves in $(1, \infty)$ exactly like the geometric Brownian motion

$$\exp\{\sigma(W_t + b't)\},$$

where $b' = \frac{b}{\sigma} - \frac{\sigma}{2}$. Equivalently, then, we could consider the Brownian motion with drift:

$$Y_t = W_t + b't,$$

killed at a rate $ke^{\sigma y}$ and reflected at 0. This will have the same mortality distribution as X_t . This makes it trivial to see that if σk is small, then for intermediate times t , such that

$$\frac{b'}{\sigma k} \gg e^{b't}$$

we will have $Y_t \approx b't/\sigma$, so the killing rate will be about $k \exp\{b't\}$.

In the notation of section 3.2 we have $B(x) = b'x$, where b' is positive. The left boundary 0 is regular, while the right boundary ∞ is natural. Since $\kappa(x) \rightarrow \infty$ as $x \rightarrow \infty$, we can apply Theorem 7, as long as $\underline{\lambda}$ is finite. This guarantees the convergence to a quasistationary distribution.

The details may be found in section 3 of [SE]. The result is that the process conditioned on survival far a long time converges to the quasistationary distribution

$$\phi(x) = \frac{x^{\frac{b}{\sigma^2} - \frac{3}{2}} K_{i\tilde{y}}\left(\frac{\sqrt{8kx}}{\sigma}\right)}{\int_0^\infty x^{\frac{b}{\sigma^2} - \frac{3}{2}} K_{i\tilde{y}}\left(\frac{\sqrt{8kx}}{\sigma}\right) dx},$$

where K is the modified Bessel function, and \tilde{y} is the smallest y such that $K'_{iy}(\sqrt{8k}/\sigma) = 0$. This function ϕ behaves asymptotically as

$$x^{\frac{b}{\sigma^2} - 2} e^{-\sqrt{8kx}/\sigma}$$

as $x \rightarrow \infty$. The asymptotic killing rate is

$$\frac{\sigma^2}{8} \left[\left(\frac{2b}{\sigma^2} - 1 \right)^2 + \tilde{y}^2 \right].$$

4.4. Multidimensional fitness. An interesting variant of the model proposed by Anderson and Weitz-Fraser, would view fitness as having several — perhaps many — components $(X_1(t), \dots, X_n(t))$, all carrying out independent Brownian motions. We think of 0 as representing the optimum, and we represent total senescence by a continuous function $f(x_1, \dots, x_n)$ which is taken to be increasing in $|x_i|$ for each i ; we assume, as well, that $\{(x_1, \dots, x_n) : f(x_1, \dots, x_n) \leq K\}$ is bounded, for each K . The process is killed at a rate $\kappa(f(x_1, \dots, x_n))$ when it is at (x_1, \dots, x_n) , but there is also a maximum senescence K , such that the process is killed as soon as its senescence reaches K . Since the state space of the process is compact, we may infer from Theorem 9 that the killing rate and the distribution of the fitness conditioned on survival converges to a limit given by the solution to the eigenvalue problem (34).

In general, explicit solutions will be difficult (though numeric solutions could be computed with standard algorithms). One case which we can solve in closed form, though, is that where $f(x_1, \dots, x_n) = x_1^2 + \dots + x_n^2$, with $n \geq 3$, and the killing occurs only when f reaches a fixed magnitude K^2 . What makes this case so straightforward

is the fact that the magnitude of the n -dimensional Brownian motion is itself a well-explored one-dimensional Markov process, known as the Bessel process of order ν , where $\nu = n/2 - 1$. The generator is

$$(39) \quad \mathcal{L}\phi(x) = \frac{1}{2}\phi''(x) + \left(\nu + \frac{1}{2}\right)x^{-1}\phi'(x).$$

We may either apply Theorem 6, with the inaccessible (entrance) boundary at 0 and the regular boundary at

The adjoint eigenvalue problem is

$$\frac{1}{2}\phi''(x) + \left(\nu + \frac{1}{2}\right)[x^{-1}\phi(x)]' + \lambda\phi(x) = 0,$$

for $x \in (0, K)$, with $\phi(K) = 0$ and $\phi'(0) = 0$. It has the general solution

$$(40) \quad x^{\nu+1} \left(c_1 J_\nu(\sqrt{2\lambda}x) + c_2 Y_\nu(\sqrt{2\lambda}x) \right),$$

in terms of the Bessel functions J_ν and Y_ν . Since $\nu > 0$, and $J_\nu(z) \sim (\frac{1}{2}z)^\nu / \Gamma(\nu+1)$ (by 9.1.7 of [AS65]), we see that $x^{\nu+1}J_\nu(\sqrt{2\lambda}x)$ has derivative 0 at $x = 0$. On the other hand, by 9.1.9 of [AS65] we see that $x^{\nu+1}Y_\nu(\sqrt{2\lambda}x)$ behaves asymptotically like a nonzero constant times x near 0, so it has a nonzero derivative at 0. Consequently, our solution to the boundary-value problem must have the form

$$\phi(x) = cx^{\nu+1}J_\nu(\sqrt{2\lambda}x).$$

The other boundary value is $\phi(K) = 0$. This means that $\sqrt{2\lambda}K$ is a zero of J_ν . The function J_ν will be positive on $(0, K)$ only if it is the smallest positive zero, conventionally denoted $j_{\nu,1}$. (In general, the i -th positive zero is denoted $j_{\nu,i}$. Thus, the limiting rate of mortality for this process is

$$\lambda = \frac{j_{\nu,1}^2}{2K^2},$$

and the senescence states of those individuals who survive until time t converges to

$$(41) \quad cx^{\nu+1}J_\nu(j_{\nu,1}x/K)$$

as $t \rightarrow \infty$.

In fact, the eigenvalue expansion may be continued to give the exact distribution of the time when the Bessel process of order ν hits K . This is given by formula

6.2.0.2 of [BS96]:

$$(42) \quad \mathbb{P}_x\{T \in dt\} = \sum_{i=1}^{\infty} \frac{j_{\nu,i} x^{-\nu} J_{\nu}(j_{\nu,i} x/K) K^{\nu-2}}{J_{\nu+1}(j_{\nu,i})} e^{-j_{\nu,i}^2 t/2K^2} dt.$$

When x (the starting point) is 0, this simplifies slightly to

$$(43) \quad \mathbb{P}_0\{T \in dt\} = \sum_{i=1}^{\infty} \frac{(j_{\nu,i})^{\nu+1}}{\Gamma(\nu+1) 2^{\nu} K^2 J_{\nu+1}(j_{\nu,i})} e^{-j_{\nu,i}^2 t/2K^2} dt.$$

4.5. The series-parallel model. Another discrete-space model that has been advanced by Gavrilov and Gavrilova in [GG91] and [GG01] represents the organism as an assemblage of independent “elements” in each of k independent “organ systems”. A system fails when all of its components has failed, but the organism dies as soon as any one of its organs fails. The failure times of the components are independent exponential random variables with expectation $1/\lambda$. (The particular assumptions that Gavrilov and Gavrilova impose on the starting condition we defer to section 5.1.)

We represent this model as a Markov process with state space k -tuples of non-negative integers. If the process is in state $(i_1, i_2, \dots, i_r, \dots, i_k)$, with all the i_j positive, the rate of transition to state $(i_1, i_2, \dots, i_r - 1, \dots, i_k)$ is $i_r \lambda$, for each $1 \leq r \leq k$.

Let T be the time of death, and let T_i be the time when component i first reaches 0. Then $T = \min T_i$. Each T_i is the sum of exponential waiting times with rates $\lambda, 2\lambda, \dots, x_i \lambda$, where x_i is the initial number of elements in system i . T_i has the same distribution as the maximum of x_i independent exponential waiting times with rate λ , so

$$\mathbb{P}\{T_i > t\} = 1 - (1 - e^{-\lambda t})^{x_i}.$$

This gives us the distribution

$$\mathbb{P}\{T > t\} = \prod_{i=1}^k (1 - (1 - e^{-\lambda t})^{x_i}).$$

The hazard rate is then given by the logarithmic derivative with respect to t :

$$(44) \quad h(t) = \sum_{i=1}^k \frac{\lambda e^{-\lambda t} x_i (1 - e^{-\lambda t})^{x_i - 1}}{1 - (1 - e^{-\lambda t})^{x_i}}$$

$$(45) \quad = kx \frac{\lambda e^{-\lambda t} (1 - e^{-\lambda t})^{x-1}}{1 - (1 - e^{-\lambda t})^x} \text{ when all } x_i \text{ have the same value } x.$$

(It is perhaps worth noting that, although great emphasis is placed on the two-stage structure of this model — multiple serial systems, each comprised of multiple parallel components — the serial systems have no effect on the hazard rate, but to multiply it by a constant.)

It follows from (45) that

$$(46) \quad \lim_{t \rightarrow \infty} h(t) = k\lambda.$$

This may also be understood in terms of a quasistationary distribution. Conditioned on a given system surviving up to time t , as t becomes very large, the number of components surviving in the system converges to 1 with high probability. Since the systems are independent, we see that the distribution of the total state converges to one wholly concentrated at $(1, 1, \dots, 1)$, the state in which all systems have one surviving component. From that state, clearly, the hazard rate is $k\lambda$.

5. INITIAL DISTRIBUTIONS

When a mathematical model succeeds in reproducing target features of the empirical data, it is natural to suppose that the model is correct in some profound sense. But mortality models are generally too vague, and leave too much latitude to arbitrary manipulation of parameters, to assign much significance to the resulting mortality distributions. Moreover, researchers typically aim to match a particular formula only in a part of the life course, and this allows for often unconscious hocus-pocus in the definition of “small t ” or “large t ”. In one case, the Brownian motion with drift, we show how a large class of mortality-time distributions, including all mixtures of gamma distributions with certain bounds on their parameters, could be the exact outcome of this model, if the initial distribution were chosen appropriately. In addition, any distribution at all could appear for small t , to any desired degree of accuracy, if we allow the drift b to be increased *ad libitum*.

5.1. Series-parallel model redux. As we intend to suggest that the freedom to choose an initial distribution (or other arbitrary parameters of a model) could create the impression of a model magically matching the empirical facts, it will perhaps be useful to consider an example in which wishful thinking, combined with loose application of initial distributions, have contrived a Gompertz curve out of

whole cloth. Here the computations which yield the desired hazard rates are wrong, and would presumably quickly have been recognized as such if the result were not otherwise so pleasing.

We return to the series-parallel model, which we described in section 4.5, and begin by explaining how its inventors derived Gompertz hazard rates in [GG91] and [GG01]. For t which are small in comparison with $1/\lambda$ — that is, times when a typical component should still be functioning — we have the approximation to first order in λt

$$(47) \quad h(t) \approx \sum_{i=1}^k x_i \lambda^{x_i} t^{x_i-1}$$

$$(48) \quad = kx\lambda^x t^{x-1} \text{ when all } x_i \text{ have the same value } x.$$

It would be tempting to meld (48) and (46), and so to imagine a hazard rate which is initially Weibull — a power of t , that is — until it gradually flattens out at a mortality plateau. The temptation becomes even greater when Gavrilov and Gavrilova in [GG01] claim that by mixing these Weibull distributions with a Poisson starting state — that is, letting the number of components initially functioning in each system be independent Poisson random variables with common expectation μ — the early hazard rate looks like

$$(49) \quad h(t) \approx k \sum_{x=1}^{\infty} \frac{e^{-\mu} \mu^x}{x!} x \lambda^x t^{x-1} = k \lambda \mu e^{\mu(\lambda t-1)},$$

which is the coveted Gompertz hazard rate.

Unfortunately, this depends on two significant errors. The approximation which gives the Weibull hazard rate, is accurate only very close to $t = 0$, while the asymptote is only relevant for large t . For intermediate values of t , the hazard rate for this model is no more similar to the Weibull or Gompertz approximation than many another curve might be. Once we have started with the assumption that $e^{\lambda t}$ is indistinguishable from $1 + \lambda t$, we cannot hope to make fine distinctions among the various powers and exponentials of t . As an example, we plot in figure 1 the curve $4t^3$ together with the correct hazard rate for $\lambda = 1$, $k = 1$, $x = 4$.

A more serious problem is the computation which underlies (49). A hazard rate is $h(t) = -F'(t)/F(t)$, where $F(t) = \text{P}\{T > t\}$, and T is the failure time. If $F(t)$ depends on a random variable X (in this case, the number of initially functioning

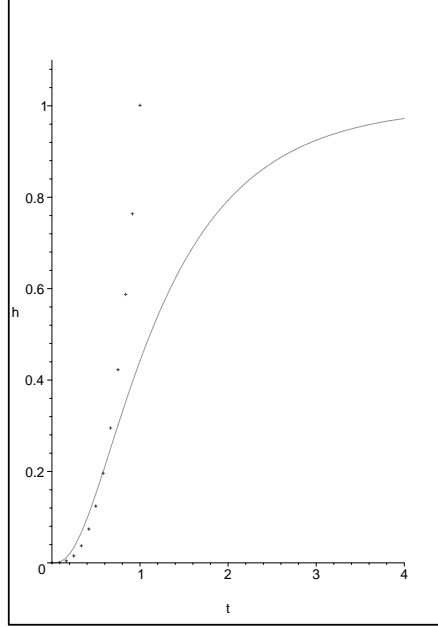


FIGURE 1. Weibull hazard rates (equation 47) with $\lambda = 1$, $k = 1$, $x = 4$ (solid curve), and the exact hazard rate for the series-parallel model (equation 44) with the same parameters (dots).

components in a system), with $P\{T > t | X = x\} = F_x(t)$ and $P\{X = x\} = p_x$, then $F(t) = \sum_x p_x F_x(t)$. We have then the hazard rate

$$h(t) = -\frac{\sum_x p_x F'_x(t)}{\sum_x p_x F_x(t)}.$$

On the other hand, the Gompertz hazard rate results from averaging the individual hazard rates

$$-\sum_x p_k \frac{F'_k(t)}{F_k(t)}.$$

If we start from the approximation (47), and mix with the Poisson distribution, we get

$$(50) \quad \frac{k}{1 - e^{-\mu}} \sum_{x=1}^{\infty} \frac{e^{-\mu} \mu^x}{x!} x \lambda (\lambda t)^{x-1} = \frac{k \lambda \mu}{e^{\mu} - 1} e^{\mu \lambda t}.$$

(The factor $(1 - e^{-\mu})^{-1}$ comes from the fact that we condition on there being at least one working component at the beginning.)

As it happens, the exact hazard rate, when computed correctly, has a simple form. The distribution function is

$$\left[\sum_{x=1}^{\infty} \frac{e^{-\mu} \mu^x}{x!(1 - e^{-\mu})} (1 - (1 - e^{-\lambda t})^x) \right]^k = \left(\frac{1 - e^{-\mu e^{-\lambda t}}}{1 - e^{-\mu}} \right)^k.$$

Thus, the hazard rate becomes

$$(51) \quad \frac{k\mu\lambda e^{-\lambda t}}{e^{\mu e^{-\lambda t}} - 1}.$$

This is very different from an exponentially increasing function. Examples are shown in figure 2. In particular, for μ smaller than about 1.8, the second derivative at $t = 0$, given by the expression

$$\frac{\lambda^2 (e^{2\mu} - 2e^{\mu} + 1 - 3\mu e^{2\mu} + 3\mu e^{\mu} + \mu^2 e^{2\mu} + \mu^2 e^{\mu})}{(e^{\mu} - 1)^3}$$

is negative. Thus, the hazard rate is already concave at $t = 0$ for these values of μ .

This is not to say that no version of this model can generate anything remotely like a Gompertz hazard rate. There are several parameters, offering ample scope for cherry-picking. In particular, if we make λ very small, say .005, this will have the effect of stretching the mortality curve out in time, creating the appearance of a fairly constant linear growth. This makes the hazard rate extremely small, so we can blow it up by choosing a very large value of k , such as 20000. We still have a very compressed hazard rate: it seems exponential for the first 75 years or so, but barely completes a single doubling in that time. This may be remedied by choosing μ somewhat larger: say 15. The result may be seen on the left of figure 3.

It might be argued that the model ought to be applied in exactly this range of parameters. However, as we have already pointed out, it is a frail defense for a model, to say that it can be compelled to approximate a line by skillful manipulation of multiple parameters. The same may be achieved with the Weibull model. For instance, if the hazard rate were given by

$$(52) \quad (.0025t + .77)^{20},$$

we get the log hazard shown on the right of figure 3. Merely matching the coarse features of the hazard rate is well known to be only a weak success of a model. What

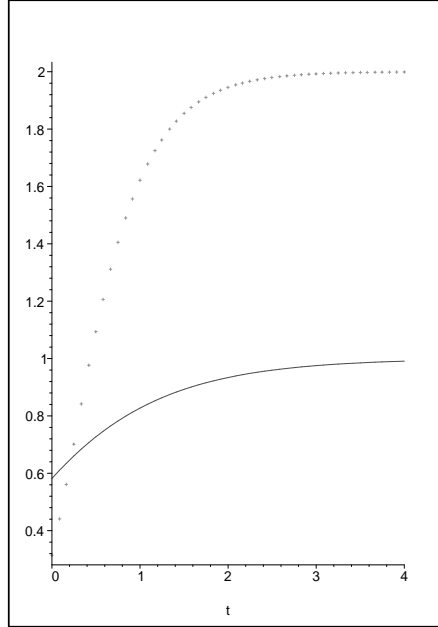


FIGURE 2. Hazard rate (equation 51) for the series-parallel process with $k = 1$, and $\lambda = 1$ (solid) or $\lambda = 2$ (dots), started with the initial number of components having a Poisson distribution with expectation $\mu = 1$ (solid) or $\mu = 3$ (dots), conditioned on at least one working component.

was promised here — erroneously — was an analytic derivation of the Gompertz curve.

5.2. Brownian motion with drift. After introducing their model for arbitrary initial distributions of fitness, Weitz and Fraser carry out their computations only for “homogeneous” populations; that is, with X_0 a deterministic constant. Anderson constrains his model similarly. In fact, though, there is no obvious justification for the starting condition to be deterministic. It turns out that the choice of starting distribution is enough to realize almost any hitting-time distribution, up to an error which can be made as small as you like, though at the expense of making the limiting mortality rate larger.

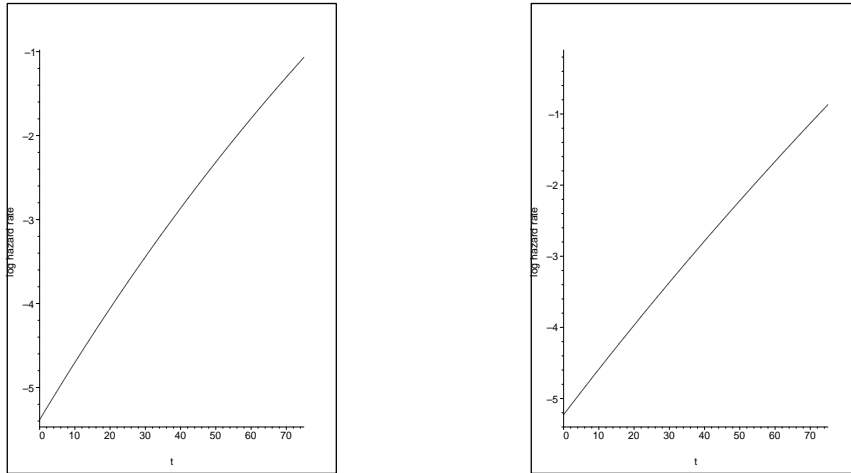


FIGURE 3. Left: Natural logarithm of the hazard rate (equation 51) for the series-parallel process with $k = 20000$, $\lambda = .005$, and $\mu = 15$, conditioned on at least one working component. Right: Natural logarithm of the Weibull hazard rate given in equation (52).

We remind the reader that the gamma distributions are a two-parameter family of distributions on the positive real line with density

$$\gamma_{r,\beta}(x) = \Gamma(r)^{-1} \beta^r x^{r-1} e^{-\beta x},$$

where the shape parameter $r \geq -1$ and the scale parameter β is any positive number. A gamma random variable has expectation r/β and variance r/β^2 . For $r = 1$, this is the exponential distribution, while large values of r converge to the normal distribution. Some examples of gamma densities are shown in figure 4.

If μ and μ^* are probability distributions on \mathbb{R} , we define the distance between them to be

$$(53) \quad d(X, Y) = \inf_{\substack{X \sim \mu \\ X^* \sim \mu^*}} |X - X^*| = \int_0^\infty |F(t) - F^*(t)| dt,$$

where F and F^* are the corresponding distribution functions. (The infimum is taken over X and X^* with distribution μ and μ^* respectively.) This means (see

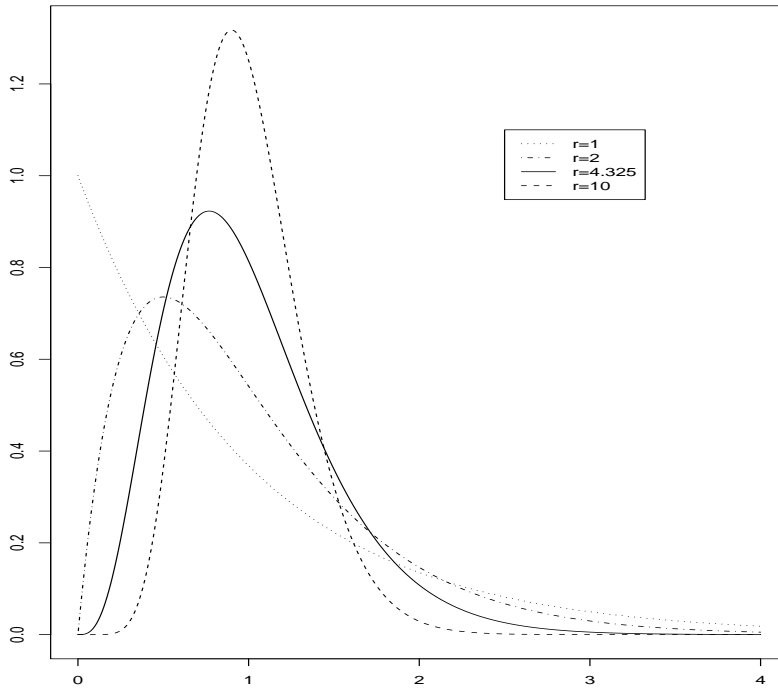


FIGURE 4. Samples of gamma densities with expectation 1

[SW86]) that μ and μ^* are close if $\int f(x)\mu(dx)$ and $\int f(x)\mu^*(dx)$ are close, whenever f is a function which does not vary too rapidly (for example, $|f'| \leq 1$).

If μ is a probability distribution on $[0, \infty)$, σ a positive constant, and b a function, we denote by $\nu_{\sigma,b}(\mu)$ the distribution of the time when a Brownian motion started in the distribution μ , with drift b and diffusion constant σ , first hits 0. We will also write $\nu_{\sigma,b}(g)$ where g is a probability density. When σ is dropped from the notation, it is implicitly assumed to be 1. We will call a distribution ν on \mathbb{R}^+ *b-attainable* if there is a distribution μ such that $\nu = \nu_b(\mu)$. It is *ϵ -approximately b-attainable* if there is a distribution μ such that $d(\nu, \nu_b(\mu)) < \epsilon$.

Note that the time of killing at 0 is unchanged by a linear rescaling of the space. This implies that $\nu_{\sigma,b}(\mu) = \nu_{b/\sigma}(\mu)$.

Our first result tells us that any target mortality-time distribution ν is ϵ -approximately b/σ -attainable when σ is a sufficiently small rescaling factor.

Theorem 10. *Suppose that ∞ is a natural boundary for the process. Assume, in addition, that b is Lipschitz, bounded away from zero, and sublinear; that is, there are positive constants α_1 and α_2 such that*

$$(54) \quad \alpha_1 \leq -b(x) \leq \alpha_2(1+x),$$

and a constant L such that

$$(55) \quad |b(x) - b(y)| \leq L|x - y| \quad \text{for all } x, y \in \mathbb{R}^+.$$

Then for any probability distribution ν on \mathbb{R}^+ such that

$$(56) \quad \int_0^\infty e^{\alpha_2 z} \sqrt{z} \nu(dz) < \infty,$$

and any positive ϵ , for every σ sufficiently small there exists a distribution μ on \mathbb{R}^+ such that $d(\nu, \nu_{b/\sigma}(\mu)) \leq \epsilon$.

In particular, any potential exit-time distribution may be approximated from some initial distribution, as long as the constant drift is made sufficiently large. The rest of the results are specific to the case of constant drift.

We remind the reader of a few facts about Laplace transforms. If μ is a probability distribution on \mathbb{R}^+ , its Laplace transform is the function

$$f(s) = \int_0^\infty e^{-sz} \mu(dz).$$

When is a given function the Laplace transform of some probability distribution? By a well-known theorem (see, for example, Theorem XIII.1.4. of [Fel71]), this is the case if and only if $\lim_{z \rightarrow 0} f(z) = 1$ and f is totally monotone (meaning that $(-1)^n f^{(n)}(s)$ is positive for all n and s ; here $f^{(n)}$ is the n -th derivative of f .) Two distributions are equal if and only if they have the same Laplace transform.

Theorem 11. *Let b be a negative constant, and let ν be a probability distribution on \mathbb{R}^+ , with Laplace transform f . Then ν is b -representable if and only if*

$$\phi(s) := f\left(\frac{s^2}{2} - bs\right)$$

is the Laplace transform of some distribution μ . This is equivalent to

$$(57) \quad \sum_{j=0}^{\lfloor n/2 \rfloor} (-1)^j \binom{n-j}{j} 4^{-j} \left(1 - \frac{b^2 - 2r}{(-b+s)^2}\right)^j \xi_{n-j}\left(\frac{s^2}{2} - bs\right) > 0$$

$$\forall s \in \mathbb{R}^+, n \in \mathbb{Z}^+,$$

where

$$\xi_k(s) := (-1)^k \frac{(s+r)^k}{k!} f^{(k)}(s) > 0.$$

In that case, μ is the desired starting distribution.

This allows us to show, by direct computation, that a given distribution is not b -attainable. For example, if we consider a logistic Gompertz distribution with $\theta = r = a = 1$, since the asymptotic hazard rate is 1, it could, in principle, be b -attainable for any $b \leq -\sqrt{2}$. But it is straightforward to compute that (57) is negative for $b = -\sqrt{2}$, $s = 0$, $n = 3$. If we let $b = -2$, we get a negative sum for $s = 0$ when $n = 19$.

On the other hand, Theorem 11 also allows us to show that a large class of distributions is b -attainable.

Corollary 12. *Let b be a fixed negative number. Any convex combination of gamma distributions with scale parameter $\beta \leq b^2/2$ and arbitrary shape parameters, is b -attainable.*

In the constant-drift setting, we can give a simple bound on the error of approximating a given distribution.

Corollary 13. *Let μ be any distribution on \mathbb{R}^+ . For any fixed negative b there exists a probability distribution μ^* on \mathbb{R}^+ such that*

$$(58) \quad \int_0^\infty x \nu_b(\mu^*)(dx) = \int_0^\infty x \mu(dx)$$

(that is, the two distributions define stopping times with the same expectation) and

$$(59) \quad d(\mu, \nu_b(\mu^*)) \leq |b|^{-1} \sqrt{2} \int_0^\infty x^{1/2} \mu(dx).$$

As long as the drift is reasonably well behaved — in particular, if the drift is constant — one could go even further, to show that the densities and the hazard rates may also be made to converge to target functions. The details are not very

enlightening, though, so we leave them out. In addition, it may reasonably be criticized, that this convergence as $b \rightarrow \infty$ is somewhat trivial, since it essentially just means that as b grows large, the process behaves more and more like a deterministic process. The target mortality is programmed into the distribution which slides down the axis, with minimal stochastic perturbation. This criticism does not affect Corollary 12, which tells us that a large class of killing-time distributions may be attained with fixed drift.

6. PROOFS OF RESULTS FROM SECTION 5.2

6.1. **Proof of Theorem 10.** Let

$$P(x) = \int_0^x \frac{dy}{b(y)},$$

μ^* the push-forward of ν by P ; that is, for any $A \subset \mathbb{R}^+$, $\mu^*(A) = \nu(P^{-1}(A))$. Let W_t be a single Brownian motion, and define $X_t^{(\sigma)}$ to be the strong solution to the SDE

$$dX_t = \sigma dW_t - b(X_t)dt$$

started in the distribution μ^* . The assumption that ∞ is a natural boundary guarantees the existence of a strong solution [KS88, Theorem 2.9].

Let $\tau^{(\sigma)}$ be the first time when $X_t^{(\sigma)}$ hits 0. Note that for $\sigma > 0$, the distribution of $\tau^{(\sigma)}$ is the same as the one we have denoted $\nu_{b/\sigma}(\mu^*)$. The only randomness in $X^{(0)}$ is the starting point, and it is easy to see that $\tau^{(0)}$ has the distribution ν . We need only to show that

$$\lim_{\sigma \rightarrow 0} d(\tau^{(\sigma)}, \tau^{(0)}) = 0.$$

where the distance between the random variables is understood to be the distance between their distributions. But for this it will suffice to show that

$$(60) \quad \lim_{\sigma \rightarrow 0} \mathbb{E}|\tau^{(\sigma)} - \tau^{(0)}| = 0.$$

Fix $\sigma > 0$, and let

$$Z_t = X_t^{(\sigma)} - X_t^{(0)}.$$

Also, let Z_t^* be a strong solution to

$$dZ_t^* = \sigma dW_t + \alpha_2(|Z_t^*| + 1)dt,$$

with initial condition $Z_0^* = Z_0$. Then Z^* and Z have the same diffusion term, and (by the Lipschitz condition) the drift of Z^* is greater. Thus, by the comparison theorem [KS88, Proposition 2.18] we see that $Z_t^* \geq Z_t$ for all $0 \leq t \leq T$ almost surely. By Gronwall's Lemma [DZ93, Lemma E.6], it follows that

$$(61) \quad \zeta := \sup\{Z_t : 0 \leq t \leq \tau^{(0)}\} \leq \sigma e^{\alpha_2 \tau^{(0)}} \cdot \sup_{0 \leq t \leq \tau^{(0)}} |W_t|.$$

Since $X^{(\sigma)}$ is a diffusion with negative drift at least α_1 , and since $X_{\tau^{(0)}}^{(\sigma)} \leq \zeta$, it must be that

$$\mathbf{E}[(\tau^{(\sigma)} - \tau^{(0)})^+ | \zeta] \leq \frac{\zeta}{\alpha_1}.$$

(That is, a diffusion with drift $-\alpha$ has an expected time of arrival at 0 no more than α^{-1} times its starting point.) Thus the expected overhang of $\tau^{(\sigma)}$ over $\tau^{(0)}$ is no more than α_1^{-1} times its distance from 0 when $X^{(0)}$ hits. Similarly, if $\tau^{(\sigma)} \leq \tau^{(0)}$, it must be that $X_{\tau^{(\sigma)}}^{(0)} \leq \zeta$. The difference between the hitting times is bounded by

$$\mathbf{E}|\tau^{(\sigma)} - \tau^{(0)}| \leq \frac{2\mathbf{E}\zeta}{\alpha_1}.$$

By (61), then, and using the reflection principle (see, for example, [KS88]) to see that

$$\mathbf{E}\left[\sup_{0 \leq t \leq s} |W_t|\right] = 2\mathbf{E}[|W_s|] = 4\sqrt{s}/\sqrt{2\pi},$$

we see that

$$\mathbf{E}|\tau^{(\sigma)} - \tau^{(0)}| \leq \frac{4\sigma}{\alpha_1} \mathbf{E}\left[\sqrt{\tau^{(0)}} e^{\alpha_2 \tau^{(0)}}\right].$$

By assumption (56) this is finite, and goes to 0 with σ .

6.2. Proof of Theorem 11. Suppose μ is a starting distribution such that $\nu_b(\mu) = \nu$, and call its Laplace transform g . For positive x , let τ_x be the time when a Brownian motion with drift $b < 0$, started at x , first hits 0. Define for positive α ,

$$\zeta_\alpha(x) := \mathbf{E}[e^{-\alpha \tau_x}].$$

By the Feynman-Kac formula [RS90, 8.10b], ζ satisfies

$$(62) \quad \frac{1}{2}\zeta_\alpha'' + b\zeta_\alpha' = \alpha\zeta_\alpha,$$

with boundary conditions $\zeta_\alpha(0) = 1$ and $\zeta_\alpha(\infty) = 0$. This yields

$$\zeta_\alpha(x) = \exp\{(-b - \sqrt{b^2 + 2\alpha})x\}.$$

Since the hitting time from a start in distribution μ has distribution ν , it must be that

$$f(\alpha) = \int_0^\infty \zeta_\alpha(x) \mu(dx) = g(b + \sqrt{b^2 + 2\alpha}).$$

Thus for s positive,

$$\phi(s) = f\left(\frac{s^2}{2} - bs\right) = g(s),$$

which is the Laplace transform of μ .

Now suppose that ϕ is the Laplace transform of a distribution μ . By the above computation, if μ is the initial distribution, and we let $\psi(\alpha)$ be the Laplace transform of the time of first hitting 0, we have

$$\psi(\alpha) = \phi(b + \sqrt{b^2 + 2\alpha}) = f(\alpha).$$

Since the hitting time has the same Laplace transform as ν , they are the same distribution.

It is straightforward to show by induction that

$$\phi^{(n)}(s) = \sum_{k=\lceil n/2 \rceil}^n \frac{n!}{2^{n-k} (2k-n)! (n-k)!} (s-b)^{2k-n} f^{(k)}\left(\frac{s^2}{2} - bs\right).$$

A change of variables $j = n - k$ shows then that the sum in (57) is precisely

$$(-1)^n (n!)^{-1} \left(\frac{s^2}{2} - bs + r\right)^n (-b+s)^{-n} \phi^{(n)}(s),$$

whose positivity for all s and n is the definition of ϕ being totally monotone, which is equivalent to ϕ being the Laplace transform of some distribution.

6.3. Proof of Corollary 12. We begin by noting that any convex combination of b -attainable distributions is also b -attainable, simply by starting from the corresponding convex combination of the starting distributions. Thus, we need only show that all gamma distributions with exponential rate $\beta \leq b^2/2$ are b -attainable. (It is also worth noting that any convolution of b -attainable distributions is also b -attainable.)

The gamma distribution with parameters (r, β) has Laplace transform

$$f(s) = \beta^r (\beta + s)^{-r}$$

Thus

$$\begin{aligned} f\left(\frac{s^2}{2} - bs\right) &= \beta^r \left(\beta + \frac{s^2}{2} - bs\right)^{-r} \\ &= (2\beta)^r \left(s - b + \sqrt{b^2 - 2\beta}\right)^{-r} \left(s - b - \sqrt{b^2 - 2\beta}\right)^{-r} \end{aligned}$$

For $\beta \leq b^2/2$, the roots are real, so each of the two factors is the Laplace transform of a gamma distribution. The product of two Laplace transforms is itself a Laplace transform (of the convolution of the two distributions), which completes the proof.

6.4. Proof of Corollary 13. Let $\beta = \sqrt{2|b|}$. Define the kernel

$$(63) \quad K_\beta(x, y) = \gamma_{\beta x, x}(y),$$

and let

$$(64) \quad g(y) := \int_0^\infty K_\beta(x, y) \mu(dx).$$

Observe first that g is a probability density, since it is nonnegative and

$$\int_0^\infty g(y) dy = \int_0^\infty \int_0^\infty K_\beta(x, y) \mu(dx) dy = 1$$

by changing the order of integration. Similarly, the expectation of μ^* is

$$\begin{aligned} \int_0^\infty yg(y) dy &= \int_0^\infty \int_0^\infty yK_\beta(x, y) \mu(dx) dy \\ &= \int_0^\infty \left(\int_0^\infty yK_\beta(x, y) dy \right) \mu(dx) \\ &= \int_0^\infty x\mu(dx) \\ &= \|\mu\|_1. \end{aligned}$$

Since g is a mixture of gamma densities with scale $\beta = b^2/2$, we know from Corollary 12 that a distribution μ^* exists such that $\nu_b(\mu^*)$ has density g . It only remains then to show that this distribution does indeed have the right distance from μ .

Let X be a random variable with distribution μ . Conditioned on X , let Y be a random variable with a gamma distribution, with parameters $(\beta X, X)$. Observe that, conditioned on X , the random variable $(X - Y)$ has expectation 0 and standard

deviation $\sqrt{x/\beta}$. Then Y has density $g(y)$ and

$$\begin{aligned} \mathbb{E}[|X - Y|] &= \mathbb{E}[\mathbb{E}[|X - Y| \mid X]] \\ &\leq \mathbb{E}[\sqrt{X/\beta}]. \end{aligned}$$

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