

Economics

A redevelopment of economic theory without parallel universes

Ole Peters and Alexander Adamou



2019/02/15 at 10:02:58

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1 Tossing a coin

In this introductory chapter we lay the conceptual foundation for the rest of what we have to say. We play a simple coin-toss game and analyze it by Monte Carlo simulation and with pen and paper. The game motivates the introduction of the expectation value and the time average, which in turn lead to a discussion of ergodic properties. We note the importance of rates of change and introduce Brownian motion and Geometric Brownian motion. Some historical perspective is provided to understand the prevalence or absence of key concepts in modern economic theory and other fields. The emphasis is on concepts, with more formal treatments and applications in later chapters.

1.1 The game

Imagine we offer you the following game: we toss a coin, and if it comes up heads we increase your monetary wealth by 50%; if it comes up tails we reduce your wealth by 40%. We're not only doing this once, we will do it many times, for example once per week for the rest of your life. Would you accept the rules of our game? Would you submit your wealth to the dynamic our game will impose on it?

Your answer to this question is up to you and will be influenced by many factors, such as the importance you attach to wealth that can be measured in monetary terms, whether you like the thrill of gambling, your religion and moral convictions and so on.

In these notes we will mostly ignore these. We will build an extremely simple model of your wealth, which will lead to an extremely simple powerful model of the way you make decisions that affect your wealth. We are interested in analyzing the game mathematically, which requires a translation of the game into mathematics. We choose the following translation: we introduce the key variable, $x(t)$, which we refer to as “wealth”. We refer to t as “time”. It should be kept in mind that “wealth” and “time” are just names that we've given to mathematical objects. We have chosen these names because we want to compare the behaviour of the mathematical objects to the behaviour of wealth over time, but we emphasize that we're building a model – whether we write $x(t)$ or wealth(time) makes no difference to the mathematics.

The usefulness of our model will be different in different circumstances, ranging from completely meaningless to very helpful. There is no substitute for careful consideration of any given situation, and labeling mathematical objects in one way or another is certainly none.

Having got these words of warning out of the way, we define our model of the dynamics of your wealth under the rules we specified. At regular intervals of duration δt we randomly generate a factor $r(t)$ with each possible value $r_i \in \{0.6, 1.5\}$ occurring with probability 1/2,

$$r(t) = \begin{cases} 0.6 & \text{with probability } 1/2 \\ 1.5 & \text{with probability } 1/2 \end{cases} \quad (1)$$

and multiply current wealth by that factor, so that

$$x(t) = r(t)x(t - \delta t). \quad (2)$$

Without discussing in depth how realistic a representation of your wealth this model is (for instance your non-gambling related income and spending are not represented in the model), and without discussing whether randomness truly exists and what the meaning of a probability is we simply switch on a computer and simulate what might happen. You may have many good ideas of how to analyze our game with pen and paper, but we will just generate possible trajectories of your wealth and pretend we know nothing about mathematics or economic theory. Figure 1 is a trajectory of your wealth, according to our computer model as it might evolve over the course of 52 time steps (corresponding to one year given our original setup).

A cursory glance at the trajectory does not reveal much structure. Of course there are regularities, for instance at each time step $x(t)$ changes, but no trend

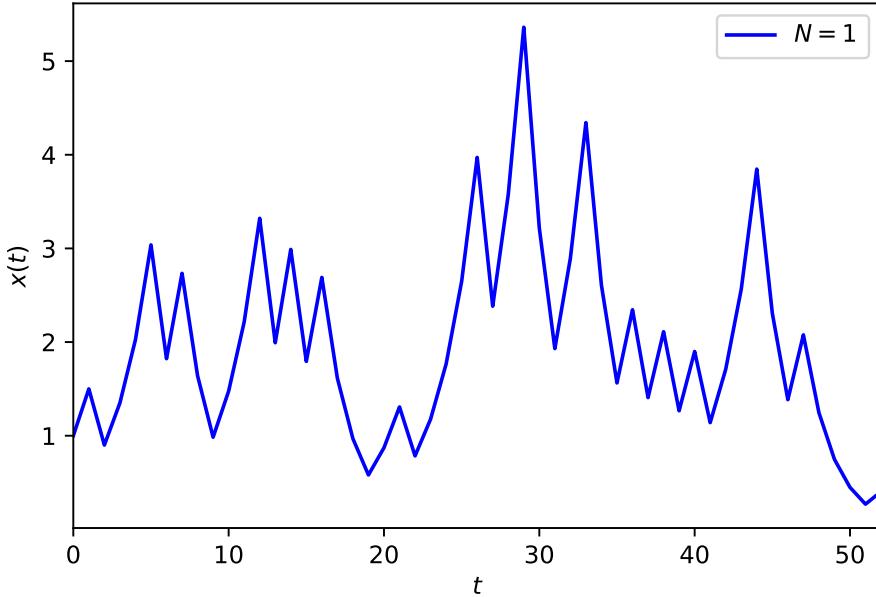


Figure 1: Wealth $x(t)$ resulting from a computer simulation of our game, repeated 52 times.

is discernible – does this trajectory have a tendency to go up, does it have a tendency to go down? Neither? What are we to learn from this simulation? Perhaps we conclude that playing the game for a year is quite risky, but is the risk worth taking?

1.1.1 Averaging over many trials

A single trajectory doesn't tell us much about overall tendencies. There is too much noise to discern a clear signal. A common strategy for getting rid of noise is to try again. And then try again and again, and look at what happens on average. For example, this is very successful in imaging – the 2014 Nobel Prize in chemistry was awarded for a technique that takes a noisy image again and again. By averaging over many images the noise is reduced and **a resolution beyond the diffraction limit is achieved**.

So let's try this in our case and see if we can make sense of the game. In Fig. 2 we average over finite ensembles of N trajectories, that is, we plot the finite-ensemble average.

DEFINITION: Finite-ensemble average

The finite-ensemble average of the quantity z at a given time t is

$$\langle z(t) \rangle_N = \frac{1}{N} \sum_i^N z_i(t), \quad (3)$$

where i indexes a particular realization of $z(t)$ and N is the number of realizations included in the average.

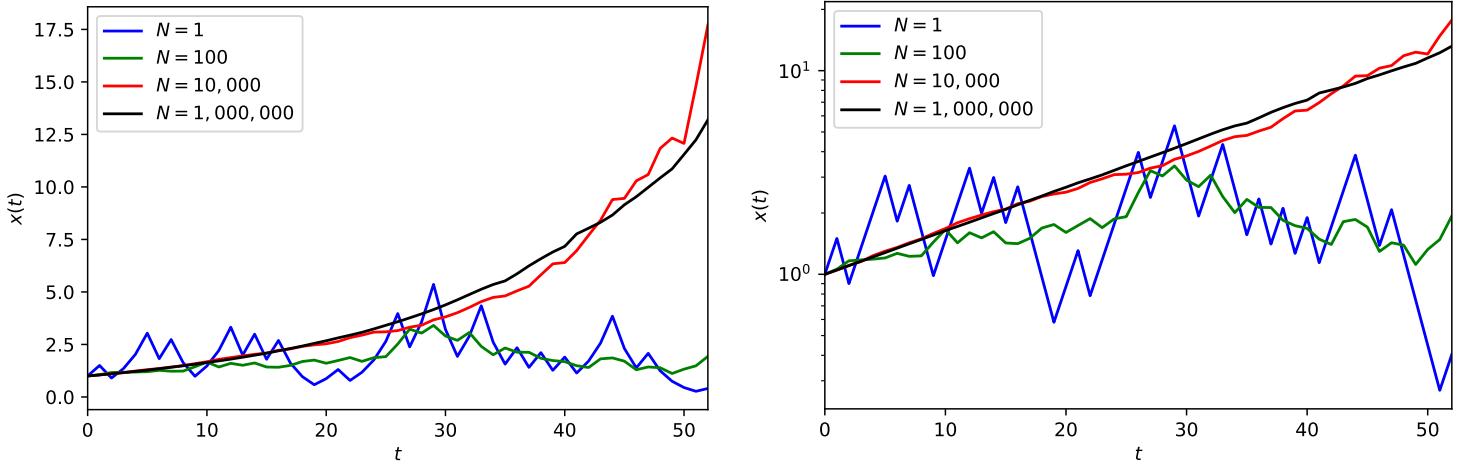


Figure 2: Partial ensemble averages $\langle x(t) \rangle_N$ for ensemble sizes $N = 1, 10^2, 10^4, 10^6$. (A) linear scales, (B) logarithmic scales.

As expected, the more trajectories are included in the average, the smaller the fluctuations of that average. For $N = 10^6$ hardly any fluctuations are visible. Since the noise-free trajectory points up it is tempting to conclude that the risk of the game is worth taking. This reasoning has dominated economic theory for about 350 years now. But it is flawed.

1.1.2 Averaging over time

Does our analysis necessitate the conclusion that the gamble is worth taking? Of course it doesn't, otherwise we wouldn't be belabouring this point. Our critique will focus on the type of averaging we have applied – we didn't play the game many times in a row as would correspond to the real-world situation of repeating the game once a week for the rest of your life. Instead we played the game many times in parallel, which corresponds to a different setup.

We therefore try a different analysis. Figure 3 shows another simulation of your wealth. This time we don't show an average over many trajectories but a simulation of a single trajectory over a long time. Noise is removed also in this case but in a different way: to capture visually what happens over a long time we have to zoom out – more time has to be represented by the same amount of space on the page. In the process of this zooming-out, small short-time fluctuations will be diminished. Eventually the noise will be removed from the system just by the passage of time.

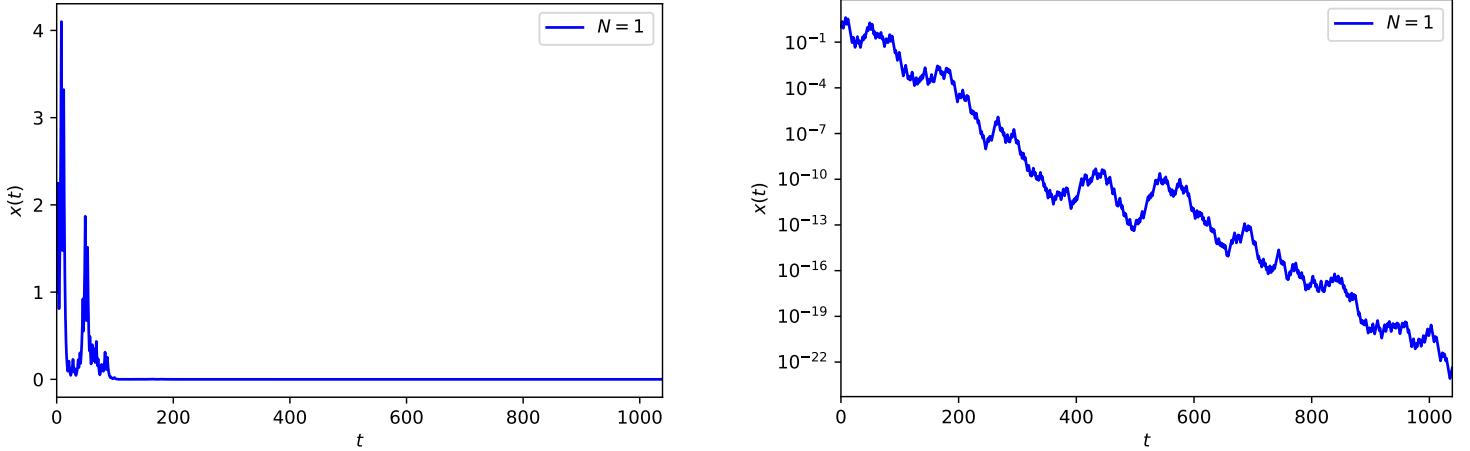


Figure 3: Single trajectory over 1,040 time units, corresponding to 20 years in our setup. (A) linear scales, (B) logarithmic scales.

Of course the trajectory in Fig. 3 is random, but the apparent trend emerging from the randomness strongly suggests that our initial analysis does not reflect what happens over time in a single system. Jumping ahead a little, we reveal that this is indeed the case. If it seems counter-intuitive then this is because our intuition is built on so-called “ergodic processes”, whereas x is non-ergodic. We will say more about this in Sec. 1.1.5. Several important messages can be derived from the observation that an individual trajectory grows more slowly (or decays faster) over time than an average of a large ensemble.

1. An individual whose wealth follows (Eq. 2) will make poor decisions if he uses the finite-ensemble average of wealth as an indication of what is likely to happen to his own wealth.
2. The performance of the average (or aggregate) wealth of a large group of individuals differs systematically from the performance of an individual’s wealth. In our case large-group wealth grows (think [Gross domestic product \(GDP\)](#)), whereas individual wealth decays.
3. For point 2 to be possible, *i.e.* for the average to outperform the typical individual, wealth must become increasingly concentrated in a few extremely rich individuals. The wealth of the richest individuals must be so large that the average becomes dominated by it, so that the average can grow although almost everyone’s wealth decays. Inequality increases in our system.

The two methods we’ve used to eliminate the noise from our system are well known. The first method is closely related to the mathematical object called the expectation value, and the second is closely related to the object called the time average.

1.1.3 Expectation value

In this section we validate Fig. 2 by computing analytically the average of $x(t)$ over infinitely many realizations, a quantity known as the expectation value. The expectation value is usually introduced as the sum of all possible values, weighted by their probabilities. We will define it as a limit instead, and then show that this limit is identical to the familiar expression.

Excursion: Random variables

We assume that you are somewhat familiar with the concept of a random variable, and we will avoid a lengthy technical discussion. Instead, we highly recommend reading the 2-page discussion in van Kampen's excellent book [?, p. 2], some of whose key points we reproduce here.

A random variable is an object Z defined by

- a set of possible values
- a probability distribution over this set.

That's it. The set may be discrete, like $\{4, 7.8, 29\}$ or the integers, \mathbb{Z} ; or it may be continuous, like the interval $(3, 12)$, or the positive reals, \mathbb{R}^+ . The **Probability density function (PDF)** is a non-negative function of the set,

$$\mathcal{P}_Z(z) \geq 0. \quad (4)$$

Note the (common) use of capital and small letters: $\mathcal{P}_Z(z)$ is the PDF of the random variable Z (capital) at value z (small). The PDF is normalized, so that the integral over the entire set is one,

$$\int \mathcal{P}_Z(z) dz = 1. \quad (5)$$

The probability (a number between 0 and 1) that z is between a and b is

$$\int_a^b \mathcal{P}_Z(z) dz. \quad (6)$$

When the set of possible values is discrete, we will write p_i to mean the probability of the j^{th} value in the set, z_i . We could also express this as an integral of the PDF over a neighborhood of z_j that includes no other possible values.

A possible value z , randomly selected in accordance with $\mathcal{P}_Z(z)$, is called an “instance” or “realization” of the random variable Z .

Of course we can define the distribution of a random variable to depend on all kinds of things – the day of the week, or the country we find ourselves in. Sometimes it will be useful to consider distributions of random numbers that depend on time, like in the case of wealth $x(t)$. By default we will assume that the distributions of random variables are time-independent, but to avoid confusion we will often make time dependence or independence explicit.

DEFINITION: Expectation value i

The expectation value of a quantity z is the large-ensemble limit of the finite-ensemble average (Eq. 3),

$$\langle z \rangle = \lim_{N \rightarrow \infty} \langle z \rangle_N. \quad (7)$$

This implies that in our first analysis of the game – by averaging over N trajectories – we were approximately using the (time-dependent) expectation value of a time-dependent random variable as a gauge of the desirability of the game. We will now prove that letting $N \rightarrow \infty$ is indeed the same as working with the more familiar definition of the expectation value.

DEFINITION: Expectation value ii

The expectation value of a quantity z that can take discrete values z_j is the sum of all possible values weighted by their probabilities p_j

$$\langle z \rangle = \sum_j p_j z_j. \quad (8)$$

If z is continuous, the expectation value is the integral

$$\langle z \rangle = \int_{-\infty}^{+\infty} s \mathcal{P}_Z(z) dz. \quad (9)$$

We now show that the two definitions of the expectation value are equivalent.

Proof. Consider the number of times the value z_j is observed in an ensemble of N instances. Call this number n_j . The finite-ensemble average can then be re-written as

$$\langle z \rangle_N = \frac{1}{N} \sum_i z_i \quad (10)$$

$$= \sum_j \frac{n_j}{N} z_j, \quad (11)$$

where the subscript i indexes a particular instance of z , and the subscript j indexes a possible value of z . The fraction $\frac{n_j}{N}$ in the limit $N \rightarrow \infty$ is the probability p_j , and we find

$$\lim_{N \rightarrow \infty} \langle z \rangle_N = \sum_j p_j z_j. \quad (12)$$

The **Left-hand side (LHS)** is the expectation value by its first definition as a limit, the **Right-hand side (RHS)** is the expectation value by its second definition as a weighted sum. This shows that the two definitions are indeed equivalent. \square

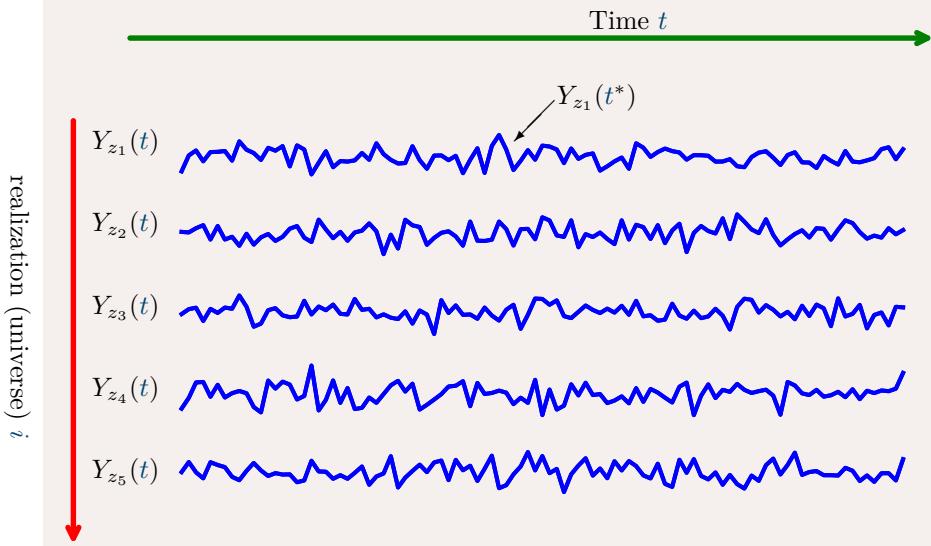
We will use the terms “ensemble average” and “expectation value” as synonyms, carefully using the term “finite-ensemble average” for finite N .

Excuse: Stochastic processes

Once again, we recommend van Kampen [?, p. 52] for a simple definition – this time of stochastic processes. Imagine we've defined a random variable, Z . Any function $Y(Z)$ is then also a random variable. A stochastic process is a special case of such a function, namely one that depends on an additional variable t , a simple scalar parameter, a number, which is interpreted as time, so we write

$$Y_Z(t) = f(Z, t). \quad (13)$$

This may not be how you think of a stochastic process, so let's illustrate this with a picture.



When we simulate stochastic processes, we often start with some value and modify it iteratively in each step of a for-loop. In each step of the for-loop we would generate a new instance of a random number and thereby construct the trajectory of the stochastic process. In (Eq. 13) it's not generated that way. Instead, in this picture, we generate an instance z of the random variable Z only once and insert that into (Eq. 13). The value z specifies a simple function of time

$$Y_z(t) = f(z, t) \quad (14)$$

meaning that all the randomness is contained in z . Once z is specified, $Y_z(t)$ is specified for all time, and we call it a “realization” or “trajectory” of the stochastic process. As an example you can think of drawing at random a single uniformly distributed real number from the interval $(0, 1)$. With probability 1, this number will be irrational and correspond to an infinite sequence of random decimal digits, which could be interpreted as a stochastic process, if t specifies the decimal place of the relevant digit.

We can also do this: fix a specific time, t^* , and consider the stochastic process at that time, $Y_Z(t^*)$. That's again a random variable, an instance

of which may be $Y_{z_1}(t^*)$.

Just as a function of a random variable is another random variable, a function of a stochastic process is another stochastic process. We will often use the noun “observable” to refer to a quantity that is derived from a stochastic process. For example, the growth rate of wealth is an observable of the wealth process.

We will suppress the random variable Z in our notation, and just write $x(t)$ for the stochastic wealth process (instead of writing $x(Z, t)$, *c.f.* (Eq. 13)).

We pretended to be mathematically clueless when we ran the simulations, with the purpose to gain a deeper conceptual understanding of the expectation value. We now compute exactly the expectation value of the stochastic process $x(t)$, instead of approximating it numerically. Consider the expectation value of (Eq. 2)

$$\langle x(t + \delta t) \rangle = \langle x(t)r(t + \delta t) \rangle. \quad (15)$$

We’ve just learned what to call objects like $r(t)$: it’s another stochastic process, albeit an especially simple one, namely one that is ergodic. We’ll explain in Sec. 1.1.5 what we mean by that, but we note here that its ensemble average is time-independent. Since $r(t + \delta t)$ is independent of $x(t)$, (Eq. 15) can be re-written as

$$\langle x(t + \delta t) \rangle = \langle x(t) \rangle \langle r \rangle. \quad (16)$$

Therefore, we can solve recursively for the wealth after T rounds, corresponding to a playing time of $\Delta t = T\delta t$:

$$\langle x(t + \Delta t) \rangle = \langle x(t + T\delta t) \rangle = x(t) \langle r \rangle^T. \quad (17)$$

δt is the duration of a single round of a gamble, while Δt is the amount of time spent gambling.

The expectation value $\langle r \rangle$ is easily found from (Eq. 1) as $\langle r \rangle = \frac{1}{2} \times 0.6 + \frac{1}{2} \times 1.5 = 1.05$. Since this number is greater than one, $\langle x(t) \rangle$ grows exponentially in time by a factor 1.05 each time unit, or expressed as a continuous growth rate, at $\frac{1}{\delta t} \ln \langle r \rangle \approx 4.9\%$ per time unit. This is what might have led us to conclude that the gamble is worth taking. Figure 4 compares the analytical result for the infinite ensemble to the numerical results of Fig. 2 for finite ensembles.

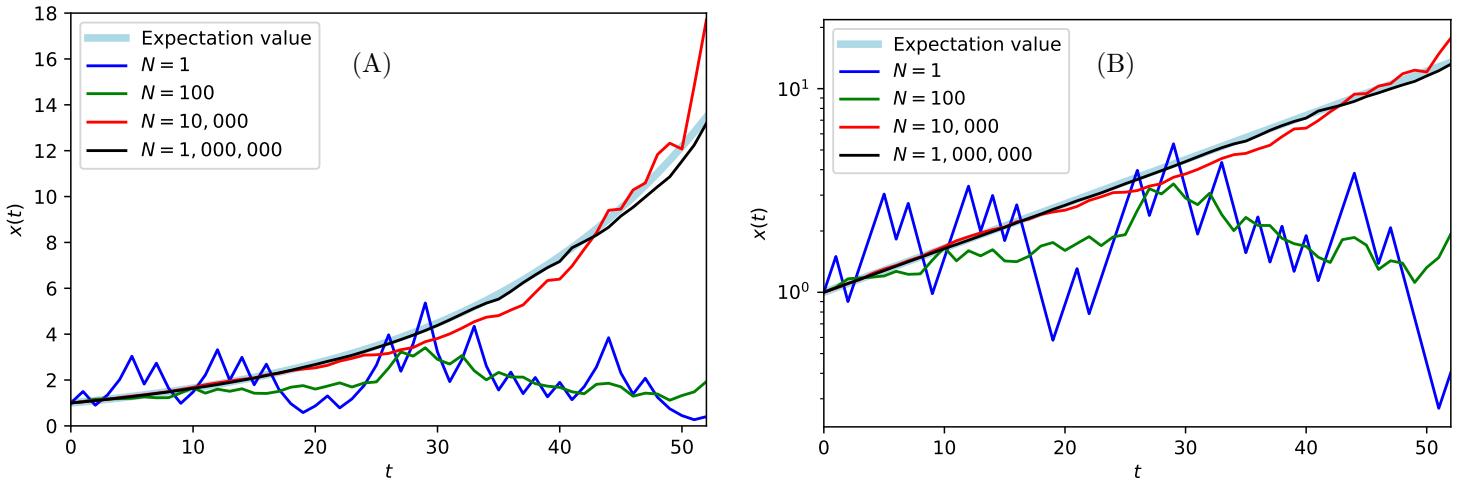


Figure 4: Expectation value (thick light blue line) and finite-ensemble averages. (A) linear scales, (B) logarithmic scales.

We stress that the expectation value is just some mathematical object – someone a long time ago gave it a suggestive name, but we certainly shouldn’t give any credence to a statement like “we expect to find $x(t) = \langle x(t) \rangle$ because it’s the expectation value.” Mathematical objects are quite indifferent to the names we give them.

History: The invention of the expectation value

Expectation values were not invented in order to assess whether a gamble is worth taking. Instead, they were developed to settle a moral question that arises in the following somewhat contrived context: imagine playing a game of dice with a group of gamblers. The rules of the game are simple: we roll the dice three times, and whoever rolls the most points gets the pot to which we’ve all contributed equal amounts. We’ve already rolled the dice twice when suddenly the police burst in because they’ve heard of our illegal gambling ring. We all avoid arrest, most of us escape through the backdoor, and to everyone’s great relief you had the presence of mind to grab the pot before jumping out of a conveniently located ground-floor window. Later that day, under the cover of dusk, we meet behind the old oak tree just outside of town to split the pot in a fair way. But hold on – what does “fair” mean here? Some of us had acquired more points than others in the first two rolls of the dice. Shouldn’t they get more? The game was not concluded, so wouldn’t it be fair to return to everyone his wager and thank our lucky stars that we weren’t arrested? Should we split the pot in proportion to each player’s points? All of these solutions were proposed [?]. The question is fundamentally moral, and there is no mathematical answer. But Blaise Pascal, now famous for addressing theological questions using expectation values, put the problem to Pierre de Fermat, and over the course of a few

months' correspondence (the two never met in person) Fermat and Pascal agreed that fairness is achieved as follows: think of all (equally likely) possible outcomes of the third round of throws of the dice, call the number of all possibilities N . Now count those possibilities that result in player j winning, call this n_j . If q is the amount of money in the pot, then we split the pot fairly by giving each player $\frac{n_j}{N} \times q$. This is $\langle q \rangle$, according to (Eq. 8), because $\frac{n_j}{N} = p_j$ is the probability that player j wins the amount q . Later researchers called this amount the “mathematical expectation” or simply “expectation value”. But this is really an unfortunate choice – no player “expected” to receive $\langle q \rangle$. Instead, each player expected to receive either nothing or q .

1.1.4 Time average

In this section we validate Fig. 3 and compute analytically what happens in the long-time limit. The blue line in Fig. 3 is not completely smooth, there's still some noise. It has some average slope, but that slope will vary from realisation to realisation. The longer we observe the system, *i.e.* the more time is represented in a figure like Fig. 3, the smoother the line will be. In the long-time limit, $\Delta t \rightarrow \infty$, the line will be completely smooth, and the average slope will be a deterministic number – in any realization of the process it will come out identical.

The dynamic is set up such that wealth at time $t + \Delta t$, where $\Delta t = T\delta t$ as before, is

$$x(t + \Delta t) = x(t) \prod_{\tau=1}^T r(t + \tau\delta t), \quad (18)$$

with the dummy variable τ indicating the round of the game. We can split this into two products, one for each possible value of $r(t)$, which we call r_1 and r_2 , *i.e.*

$$r(t) = \begin{cases} r_1 & \text{with probability } p_1 \\ r_2 & \text{with probability } p_2 = 1 - p_1. \end{cases} \quad (19)$$

Let's denote the number of occurrences of r_1 by n_1 and of r_2 by n_2 , so that

$$x(t + \Delta t) = x(t) r_1^{n_1} r_2^{n_2}. \quad (20)$$

We denote by \bar{r} the effective factor by which $x(t)$ is multiplied per round when the change is computed over a long time, *i.e.* $x(t + \Delta t) \sim x(t)(\bar{r})^T$ as $\Delta t \rightarrow \infty$. This quantity is found by taking the T^{th} root of $\frac{x(t+\Delta t)}{x(t)}$ and considering its long-time limit:

$$\bar{r} = \lim_{\Delta t \rightarrow \infty} \left(\frac{x(t + \Delta t)}{x(t)} \right)^{1/T} \quad (21)$$

$$= \lim_{T \rightarrow \infty} r_1^{n_1/T} r_2^{n_2/T}. \quad (22)$$

Identifying $\lim_{T \rightarrow \infty} n_1/T$ as the probability p_1 for r_1 to occur (and similarly $\lim_{T \rightarrow \infty} n_2/T = p_2$) this is

$$\lim_{T \rightarrow \infty} \left(\frac{x(t + T\delta t)}{x(t)} \right)^{1/T} = (r_1 r_2)^{1/2}, \quad (23)$$

or $\sqrt{0.9} \approx 0.95$, *i.e.* a number smaller than one, reflecting decay in the long-time limit for the individual trajectory. The trajectory in Fig. 3 was not a fluke: *every* trajectory will decay in the long run at a rate of $(r_1 r_2)^{1/2}$ per round.

Figure 5 (B) compares the trajectory generated in Fig. 3 to a trajectory decaying exactly at rate \bar{r} and places it next to the average over a million systems.

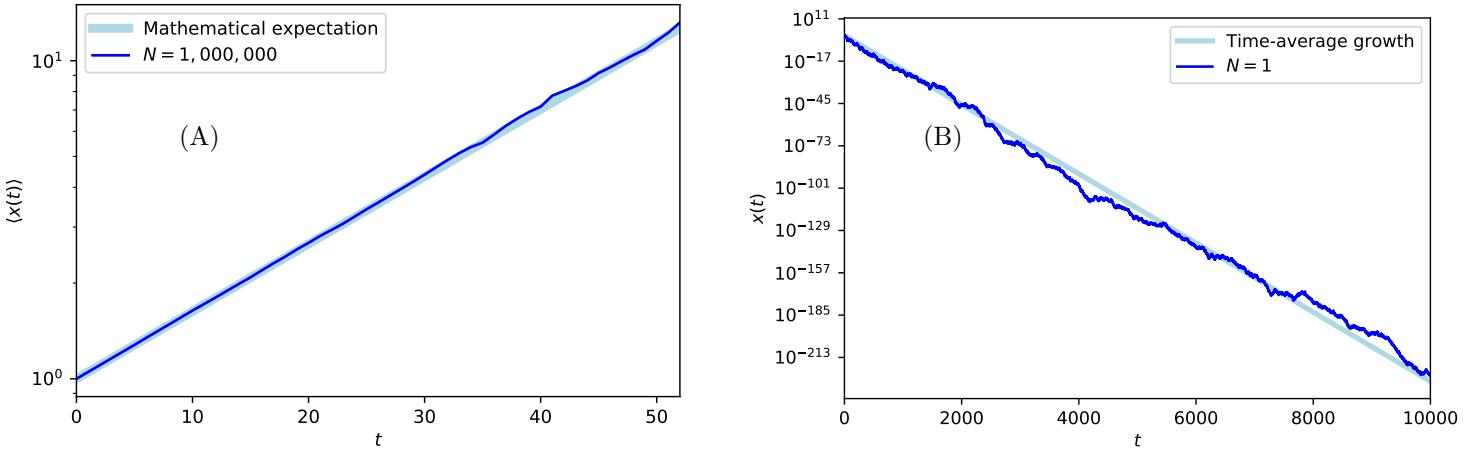


Figure 5: (A) Finite-ensemble average for $N = 10^6$ and 52 time steps, the light blue line is the expectation value.² (B) A single system simulated for 10,000 time steps, the light blue line decays exponentially with the time-average decay factor \bar{r} in each time step.

Excursion: Scalars

$r(t)$ is a random variable, whereas both $r_{\langle \rangle}$ and \bar{r} are scalars. Scalars have the so-called “transitive property” that is heavily relied upon in economic theory. Let a_i be a set of scalars. Transitivity means that if $a_1 > a_2$ and $a_2 > a_3$ we have $a_1 > a_3$. Notice that we cannot rank random variables in such a way. The “greater than” relation, $>$, is not defined for a pair of random variables, which is the mathematical way of saying that it is difficult to choose between two gambles, and it is why we went to the trouble of removing the randomness from the stochastic process $x(t)$. Removing randomness by averaging always involves a limiting process, and results are said to hold “with probability one”. In the case of $r_{\langle \rangle}$ we considered the infinite-ensemble limit, $N \rightarrow \infty$, and in the case of \bar{r} we considered the infinite-time limit, $\Delta t \rightarrow \infty$. If we use the scalars a_i to represent preferences, we can test for consistency among preferences. For instance, in such a model world where preferences are represented by scalars, the facts that “I prefer kangaroos to Beethoven” and “I prefer mango chutney to kangaroos” imply the fact “I prefer mango chutney to Beethoven”. Translating back to reality, economists like to call individuals who make the first two

statements but not the third “irrational.”

Because transitivity makes for a nicely ordered world, it is useful to find scalars to represent preferences. We are skeptical about the attempt to map all preferences into scalars because the properties of mango chutney are too different, *qualitatively*, from the properties of Beethoven. We will restrict our analysis to money – the amount of money we will receive is random and this introduces a complication, but at least we know how to compare one amount to another in the limit of no randomness – there is no qualitative differences between \$1 and \$3, only a quantitative difference.

Both $r_{\langle\rangle}$ and \bar{r} are scalars, and both are therefore potentially powerful representations of preferences. Your decision whether to accept our gamble could now be modelled as a choice between the value of the scalar \bar{r} if you do not accept our game, namely $a_1 = 1$, and the value of the scalar \bar{r} if you do accept, namely approximately $a_2 = 0.95$. In this model of your decision-making you would prefer not to play because $1 > 0.95$.

There are two averages, $r_{\langle\rangle}$ and \bar{r} that we have determined numerically and analytically. Neither average is “wrong” in itself; instead each average corresponds to a different property of the system. Each average is the answer to a different question. Saying that “wealth goes up, on average” is clearly meaningless and should be countered with the question “on what type of average?”

History: William Allen Whitworth

$r_{\langle\rangle}$ and \bar{r} are two different properties of the game. $r_{\langle\rangle}$ is the large-ensemble limit, \bar{r} is the long-time limit, of wealth growth it induces. The Victorian mathematician William Allen Whitworth postulated \bar{r} as the relevant property for an individual deciding whether to take part in a repeated gamble. He used this knowledge to write an appendix entitled “The disadvantage of gambling” to the 1870 edition of his book “Choice and Chance” [?]. He phrased his argument in terms of the difference of two squares. Imagine that you either win or lose, with equal probability, an amount $\epsilon x(t)$ in each round of a game. In the long run, positive and negative changes will occur equally frequently, and to determine the overall effect we just need to consider the effect of one positive and one negative change in a row. Over one up and one down-move wealth changes by the factor

$$(1 + \epsilon)(1 - \epsilon) = 1 - \epsilon^2. \quad (24)$$

This factor is clearly less than one, meaning that what’s often called a “fair gamble” – one that does not change the expectation value of the gambler’s wealth – leads to an exponential decay of his wealth over time. Hence the title of the appendix “The disadvantage of gambling.” We will see in Sec. 1.4 that Whitworth’s work captured the essence of Itô’s famous 1944 discovery [?] that was to form the basis of much of financial mathematics.

Whitworth was arguing against a dogma of expectation values of wealth, that had been established almost immediately following Fermat and Pascal’s work. He hoped to show mathematically that gambling may not be a good idea even if the odds are favourable, and was a proponent of the notion that commerce should and does consist of mutually beneficial inter-

actions rather than one winner and one loser. In the end his voice was not heard in the economics community. His main career was as a priest at All Saints Church in London's Margaret Street, only a 22 minute stroll away from the London Mathematical Laboratory, according to Google.

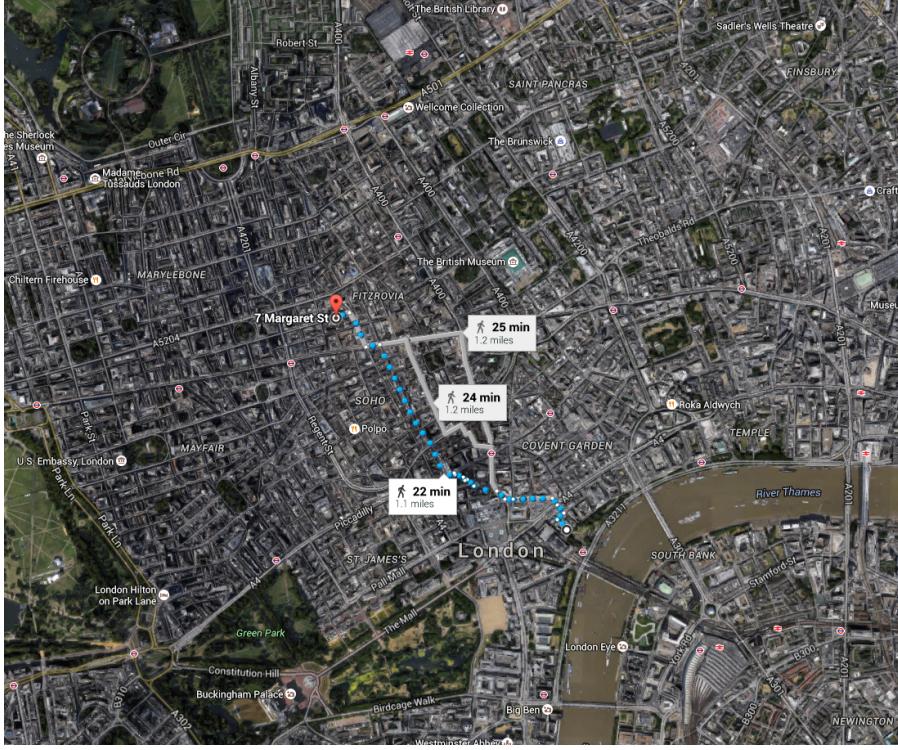


Figure 6: Location of All Saints Church and the London Mathematical Laboratory.

An observable that neatly summarises the two different aspects of multiplicative growth we have illustrated is the multiplicative (exponential) growth rate, observed over finite time Δt , in a finite ensemble of N realisations

$$g_m(\langle x(t) \rangle_N, \Delta t) = \frac{\Delta \ln \langle x \rangle_N}{\Delta t}, \quad (25)$$

where the Δ in the numerator corresponds to the change over the Δt in the denominator. For N and Δt finite this is a random variable. The relevant scalars arise as two different limits of the same stochastic object. The exponential growth rate of the expectation value (that's also $\frac{1}{\delta t} \ln \langle r \rangle$) is

$$\bar{g}_{\langle \rangle} = \lim_{N \rightarrow \infty} g_m, \quad (26)$$

and the exponential growth rate followed by every trajectory when observed for a long time (that's also $\frac{1}{\delta t} \ln \bar{r}$) is

$$\bar{g} = \lim_{\Delta t \rightarrow \infty} g_m. \quad (27)$$

We can also write (Eq. 25) as a sum of the logarithmic differences in the T individual rounds of the gamble that make up the time interval $\Delta t = T\delta t$

$$g_m(\langle x(t) \rangle_N, \Delta t) = \frac{1}{T\delta t} \sum_{\tau=1}^T \Delta \ln \langle x(t + \tau\delta t) \rangle_N. \quad (28)$$

This leads us to a technical definition of the time average.

DEFINITION: Finite-time average

The “finite-time average” of the quantity $x(t)$ is

$$\bar{x}_{\Delta t} = \frac{1}{\Delta t} \int_t^{t+\Delta t} x(s) ds. \quad (29)$$

If x only changes at $T = \Delta t/\delta t$ discrete times $t + \delta t, t + 2\delta t, \text{ etc.}$, then this can be written as

$$\bar{x}_{\Delta t} = \frac{1}{T\delta t} \sum_{\tau=1}^T x(t + \tau\delta t). \quad (30)$$

DEFINITION: Time average

The “time average” is the long-time limit of the finite-time average

$$\bar{x} = \lim_{\Delta t \rightarrow \infty} \bar{x}_{\Delta t}. \quad (31)$$

According to this definition, \bar{g} is the time average of the observable $\frac{\delta \ln x}{\delta t}$. It can be shown that the time-average growth rate of a single trajectory is the same as that of a finite-ensemble average of trajectories, $\lim_{\Delta t \rightarrow \infty} \frac{\Delta \ln x}{\Delta t} = \lim_{\Delta t \rightarrow \infty} \frac{\Delta \ln \langle x \rangle_N}{\Delta t}$, [?].

Excursion: Dimensional analysis

We will often and without qualm write the expression $\Delta \ln x$. Dimensional analysis suggests to think about this expression carefully, at least once. This may seem pedantic but the absence of this pedantry has caused sufficient confusion in economic theory for us to risk antagonizing you. “Dimension” in this context is closely related to the concept of “unit” – for instance, a dollar is a money unit, and the dimension function for money tells us how to convert from one currency into another. Similarly, length may have the unit “meter”, and the dimension function for length tells us how to convert between different systems of units, such as meters and yards. We can only point to the subject here and recommend the book by Barenblatt for a comprehensive treatment [?]. Dimensional analysis is a deeply fascinating and powerful tool that every physicist is drilled to use at all times. Taylor famously used it to compute the energy released by an early nuclear explosion at the Trinity site near Alamogordo, New Mexico, based on some grainy pictures published by Life magazine, at least that’s

the legend [?, ?]. Fluid dynamicists in general use it to find meaningful quantities to distinguish different types of flow. In many problems involving random walks dimensional analysis immediately reveals scaling properties, supposed solutions to many problems can be seen at a glance to be wrong, and, conversely some complicated-looking problems can be solved as if by magic just by appealing to dimensional analysis.

Barenblatt shows in his book that the dimension function must be a (scale-free) power-law monomial if there is to be no distinguished system of units. We can all agree that the unit of money is physically irrelevant – I can do exactly the same with the pennies in my bank account as I can do with the pounds those pennies correspond to. Since this is so, for functions of monetary amounts to be physically meaningful we want them to be power-law monomials. An amount of square-dollars, $\2 , may be meaningful, but an amount of logarithmic or exponential dollars cannot be meaningful. Hence $\ln(\textcolor{blue}{x})$ on its own is just some symbol spat on a page by a printer, but it has no physical meaning. The reason we’re comfortable writing $\Delta \ln \textcolor{blue}{x}$ is the unique property of the logarithmic function

$$\ln \textcolor{blue}{x}_1 - \ln \textcolor{blue}{x}_2 = \ln \left(\frac{\textcolor{blue}{x}_1}{\textcolor{blue}{x}_2} \right). \quad (32)$$

The quantity in brackets on the RHS is always dimensionless, it’s a pure number because the dimension functions of two different values of $\textcolor{blue}{x}$ always cancel out. So do the units: $\$/\$ = 1/2$, which is a pure number without units. We will see that indeed only differences in logarithms of $\textcolor{blue}{x}$ will appear in these lecture notes or in any other reasonable lecture notes. Pedantically, we would refuse to write $\Delta \ln(\textcolor{blue}{x})$ and insist on writing $\ln \left(\frac{\textcolor{blue}{x}_1}{\textcolor{blue}{x}_2} \right)$. Since the first notation is shorter and one can make formal arguments for its validity, we are happy to use it here.

The issue is related to a result obtained by von Neumann and Morgenstern in their famous book [?]: only differences in utility functions can have physical meaning.

1.1.5 Ergodic observables

We have encountered two types of averaging – the ensemble average and the time average. In our case – assessing whether it will be good for you to play our game, the time average is the interesting quantity because it tells you what happens to your wealth as time passes. The ensemble average is irrelevant because you do not live your life as an ensemble of many yous who can average over their wealths. Whether you like it or not, you will experience yourself owning your own wealth at future times; whether you like it not, you will never experience yourself owning the wealth of a different realization of yourself. The different realizations, and therefore the expectation value, are fiction, fantasy, imagined.

We are fully aware that it can be counter-intuitive that with probability one, a different rate is observed for the expectation value than for any trajectory over time. It sounds strange that the expectation value is completely irrelevant to the problem. A reason for the intuitive discomfort is history: since the 1650s we have been trained to compute expectation values, with the implicit belief that they will reflect what happens over time. It may be helpful to point out

that all of this trouble has a name that's well-known to certain people, and that an entire field of mathematics is devoted to dealing with precisely this problem. The field of mathematics is called "ergodic theory." It emerged from the question under what circumstances the expectation value is informative of what happens over time, first raised in the development of statistical mechanics by Maxwell and Boltzmann starting in the 1850s.

History: Randomness and ergodicity in physics

The 1850s were about 200 years after Fermat and Pascal introduced expectation values into the study of random systems. Following the success of Newton's laws of motion, established around the same time as the expectation value, the notion of "proper science" had become synonymous with mechanics. Mechanics had no use for randomness and probability theory, and the success of mechanics was interpreted as a sign that the world was deterministic and that sooner or later we would understand what at the time still seemed random. At that point probability theory would become obsolete.

When Boltzmann hit upon the ingenious idea of introducing randomness into physics, to explain the laws of thermodynamics in terms of the underlying dynamics of large numbers of molecules, he was fighting an uphill battle. Neither molecules nor randomness were much liked in the physics community, especially in continental Europe, right up until the publication of Einstein's 1905 paper on diffusion [?]. Boltzmann had to be more careful than Fermat and Pascal. He had to pre-empt predictable objections from his peers, and the question of ergodicity had to be answered – the usefulness of probability theory relies heavily on expectation values, but as we have seen, they are averages over imagined future states of the universe. Boltzmann's critics were aware of this and were not shy to voice their concerns. Under what circumstances are expectation values meaningful? Boltzmann gave two answers. Firstly, expectation values are meaningful when the quantity of interest really is an average (or a sum) over many approximately independent systems. An average over a finite ensemble will be close to the expectation value if the ensemble is large enough. Secondly, expectation values are meaningful, even if only a single system exists, if they reflect what happens over time.

Boltzmann called a system "ergodic"^a if the possible states of the system could be assigned probabilities in such a way that the expectation value of any observable with respect to those probabilities would be the same as its time average with probability 1.

Our setup requires us to be more modest, and we will speak of specific ergodic observables (not of ergodic systems) if their ensemble and time averages are the same.

^aThe word "ergodic" was coined by Boltzmann. He initially proposed the word "monodic", from Greek *μονος* (unique) + *οδος* (path) suggesting that a single path when followed for a sufficiently long time will explore all there is to explore and reflect what happens in an ensemble. The term "ergodic" refers to the specific system Boltzmann was considering, namely an energy (*εργον*) shell across which a path is being traced out.

To convey concisely that we cannot use the expectation value and the time average interchangeably in our game, we would say "*x* is not ergodic."

DEFINITION: Ergodic property

In these notes, an observable A is called ergodic if its expectation value is constant in time and its time average converges to this value with probability one^a

$$\lim_{\Delta t \rightarrow \infty} \frac{1}{\Delta t} \int_t^{t+\Delta t} A(s) ds = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_i^N A_i(t). \quad (33)$$

^aSome researchers would call A “mean ergodic” and require further observables derived from it to be (mean) ergodic in order to call A “wide-sense ergodic.” This extra nomenclature is not necessary for our work, but we leave a footnote here to avoid confusion.

The **RHS** of (Eq. 33) is evaluated at time t , and unlike the **LHS** could be a function of time. For now, we will restrict ourselves to a setup where that is not the case, *i.e.* where the ergodic property holds at all times. In Sec. 4.2.6 we will discuss transient behavior, where the distribution of A is time dependent, and the expectation value only converges to the time-average in the $t \rightarrow \infty$ limit.

In terms of random variables, Z , and stochastic processes, $Y_Z(t)$, the ergodic property can be visualized as in Fig. 7. Averaging a stochastic process over time or over the ensemble are completely different operations, and only under very rare circumstances (namely under ergodicity) can the two operations be interchanged.

We stress that in a given setup, some observables may have the ergodic property even if others do not. Language therefore must be used carefully. Saying our game is non-ergodic really means that some key observables of interest, most notably wealth x , are not ergodic. Wealth $x(t)$, defined by (Eq. 1), is clearly not ergodic – with $A = x$ the **LHS** of (Eq. 33) is zero, and the **RHS** is not constant in time but grows. The expectation value $\langle x \rangle(t)$ is simply doesn’t give us the relevant information about the temporal behavior of $x(t)$.

This does not mean that no ergodic observables exist that are related to x . Such observables do exist, and we have already encountered two of them. In fact, we will encounter a particular type of them frequently – in our quest for an observable that tells us what happens over time in a stochastic system we will find them automatically. However, again, the issue is subtle: an ergodic observable may or may not tell us what we’re interested in. It may be ergodic but not indicate what happens to x . For example, the multiplicative factor $r(t)$ is an ergodic observable that reflects what happens to the expectation value of x , whereas per-round changes in the logarithm of wealth, $\delta \ln x = \ln r$, are also ergodic and reflect what happens to x over time.

Proposition: $r(t)$ and $\delta \ln x$ are ergodic.

Proof. According to (Eq. 7) and (Eq. 3), the expectation value of $r(t)$ is

$$\langle r \rangle = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_i^N r_i, \quad (34)$$

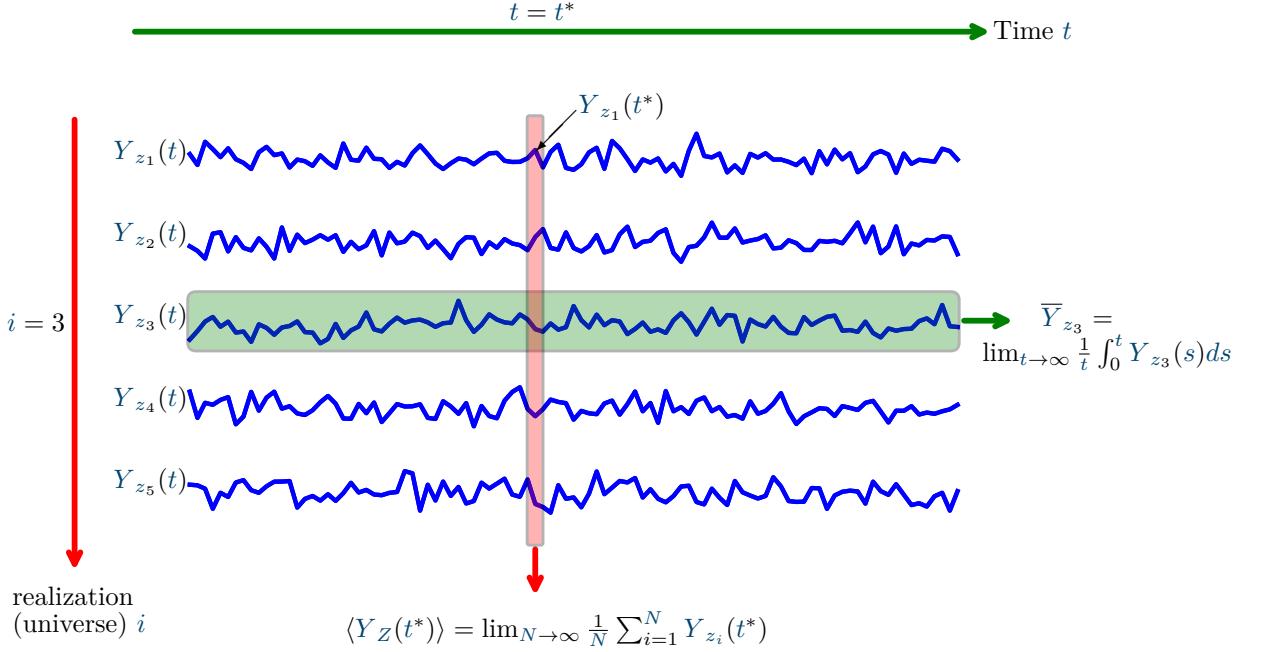


Figure 7: Extending the figure on p. 10, averaging over time means averaging along one trajectory from left to right; averaging over the ensemble means averaging at a fixed time across different trajectories from top to bottom.

and, according to (Eq. 30), the time average of $r(t)$ is

$$\bar{r} = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{\tau}^T r_{\tau}, \quad (35)$$

where we have written $r_{\tau} = r(t + \tau\delta t)$ to make clear the equivalence between the two expressions. The only difference between the two expressions is the label we have chosen for the dummy variable (i in (Eq. 34) and τ in (Eq. 35)). Clearly, the expressions yield the same value. $r(t)$ takes independent identically distributed values.

The same argument holds for $\delta \ln x$. \square

Whether we consider (Eq. 35) an average over time or over an ensemble is only a matter of our choice of words.

$\langle \delta \ln x \rangle$ is important, historically. Daniel Bernoulli noticed in 1738 [?] that people tend to optimize $\langle \delta \ln x \rangle$, whereas it had been assumed that they should optimize $\langle \delta x \rangle$. Unaware of the issue of ergodicity (200 years before the concept was discovered and the word was coined), Bernoulli had no good explanation for this empirical fact and simply stated that people tend to behave as though they valued money non-linearly. We now know what is actually going on: δx is not ergodic, and $\langle \delta x \rangle$ is of no interest – it doesn't tell us what happens over time. However, $\delta \ln x$ is ergodic, $\langle \delta \ln x \rangle$ specifies what happens to x over time, and it is the right object to optimize.

Ergodicity is related to stationarity but they are not the same concept. As an illustration, consider the following process: $f(t) = z_i$, where z_i is an instance of a random variable Z . To be explicit, this means a realization of the stochastic process $f(t)$ is generated as follows: we generate the random instance z_i once, and then fix $f(t)$ at that value for all time. The distribution of $f(t)$ is independent of t and in that sense $f(t)$ is stationary. Averaging over the ensemble, we obtain $\langle f(t) \rangle = \langle z \rangle$, whereas averaging over time in the i^{th} trajectory gives $\bar{f} = z_i$. Thus the process is stationary but not ergodic.

1.2 Rates

This section is a preview of an in-depth discussion of growth rates in Sec. 2. The ergodic observable $\delta \ln x$, identified in the previous section, is basically a rate. Dividing it by the duration of the gamble, we obtain exactly the exponential growth rate of x , namely $\frac{\delta \ln x}{\delta t}$. Finding good growth rates will be important, wherefore we now discuss the notion of a rate and the notion of time independence. To do this properly let's think about the basic task of science. This may be described as the search for stable structure. Science attempts to build models of the world whose applicability does not vary over time. This doesn't mean that the world doesn't change, but the way in which the models describe change does not change. The model identifies something stable. This is implied by the fact that we can write equations (or English sentences) in ink on paper, with the equation (or sentence) remaining useful over time. The ink won't change over time, so if an article written in 1905 is useful today then it must describe something that hasn't changed in the meantime. These "somethings" are often somewhat grandiosely called laws of nature.

Newton's laws are a good illustration of this. They are part of mechanics, meaning that they are an idealized mathematical model of the behavior of positions, time, and masses. For instance, Newton's second law, $F = m \frac{d^2 x}{dt^2}$, states that the mass multiplied by the rate of change of the rate of change of its position equals the force. The law is an unchanging law about positions, time, and masses, but it does not say that positions don't change, it doesn't even say that rates of change of positions don't change. It does say that the rate of change of the rate of change of a position remains unchanged so long as the force and the mass remain unchanged. Newton's deep insight was to transform an unstable thing – the position of a mass – until it became stable: he fixed the force and considered rates of changes of rates of changes, et voilá!, a useful equation could be written down in ink, remaining useful for 350 years so far.

Like Newton's laws (a mathematical model of the world), our game is a prescription of changes. Unlike Newton's laws it's stochastic, but it's a prescription of changes nonetheless. Our game is also a powerful mathematical model of the world, as we will see in subsequent lectures.

We're very much interested in changes of x – we want to know whether we're winning or losing – but changes in x are not stable. Under the rules of the game the rate of change of wealth, $\frac{\delta x(t)}{\delta t}$, is a different random variable for each t because it is proportional to $x(t)$. But not to worry, in Newton's case changes in the position are not stable either, even in a constant force field. Nonetheless Newton found a useful stable property. Maybe we can do something similar. We're looking for a function $v(x)$ that satisfies two conditions: it should

indicate what happens to x itself, and its random changes should be instances of a time-independent random variable.

The first condition is that $v(x)$ must tell us whether $x(t)$ is growing or shrinking – this just means that $v(x)$ has to be monotonic in x . We know that there is something time-independent about x because we were able to write down in ink how x changes. So we only need to find the monotonic function of x whose additive changes inherit the time-independence of the ink in (Eq. 1). The game is defined by a set of factors of change in $x(t)$, (Eq. 2). Therefore, the fractional change in x , namely $r(t) = \frac{x(t+\delta t)}{x(t)}$, comes from a time-independent distribution. Which function responds additively to a multiplicative change in its argument? The answer is the logarithm, *i.e.* only the logarithm satisfies

$$v[x(t + \delta t)] - v[x(t)] = v\left(\frac{x(t + \delta t)}{x(t)}\right) \quad (36)$$

and we conclude that for our game $v(x) = \ln x$. For multiplicative dynamics, *i.e.* if $\frac{x(t+\delta t)}{x(t)}$ is stationary, the expectation value of the rate of change of the logarithm of $x(t)$ determines whether the game is long-term profitable for an individual.

More generally, when evaluating a gamble that is represented as a stochastic process

1. Find a monotonically increasing function $v[x(t)]$ such that $\frac{\delta v[x(t)]}{\delta t}$ are independent instances of a stationary random variable.
2. Compute the expectation value of $\frac{\delta v[x(t)]}{\delta t}$. If this is positive then $x(t)$ grows in the long run, if it is negative then $x(t)$ decays.

This is discussed in detail in Sec. 2.

1.3 Brownian motion

In the previous section we established that the discrete increments of the logarithm of x , which we called v , are instances of a time-independent random variable in our game. A quantity for which this is the case performs a random walk. Indeed, the blue line for a single system in Fig. 2 (B) shows 52 steps of a random walk trajectory. Random walks come in many forms – in all of them v changes discontinuously by an amount δv drawn from a time-independent distribution, over time intervals which may be regular or which may be drawn from a time-independent distribution themselves.

We are interested only in the simple case where v changes at regular intervals, $\delta t, 2\delta t, \dots$. For the distribution of increments we only insist on the existence of the variance, meaning we insist that $\text{var}(\delta v) = \langle \delta v^2 \rangle - \langle \delta v \rangle^2$ be finite. The change in v after a long time is then the sum of many independent instances of increments,

$$v(t + T\delta t) - v(t) = \sum_i^T \delta v_i. \quad (37)$$

The Gaussian central limit theorem tells us that such a sum, properly rescaled, will be Gaussian distributed

$$\lim_{T \rightarrow \infty} \frac{1}{\sqrt{T}} \sum_i^T \delta v_i - T \langle \delta v \rangle \sim \mathcal{N}(0, \text{var}(\delta v)), \quad (38)$$

where we call $\frac{\langle \delta v \rangle}{\delta t}$ the drift term. The logarithmic change in the long-time limit that was of interest to us in the analysis of the coin toss game is thus Gaussian distributed.

Let's also ask about the re-scaling that was applied in (Eq. 38). Scaling properties are very robust, and especially the scaling of random walks for long times will be useful to us. We work with the simplest setup: we start at zero, $v(0) = 0$, and in each time step, we either increase or decrease v by 1, with probability 1/2. We are interested in the variance of the distribution of v as T increases, which we obtain by computing the first and second moments of the distribution. The expectation value (the first moment) of v is $\langle v \rangle(T) = 0$, by symmetry for all times. We obtain the second moment by induction³: Whatever the second moment, $\langle v(T)^2 \rangle$, is at time T , we can write down its value at time $T + 1$ as

$$\langle v(T+1)^2 \rangle = \frac{1}{2} [\langle (v(T)+1)^2 \rangle + \langle (v(T)-1)^2 \rangle] \quad (39)$$

$$= \frac{1}{2} [\langle v(T)^2 + 1 + 2v(T) \rangle + \langle (v(T)^2 + 1 - 2v(T)) \rangle] \quad (40)$$

$$= \langle v(T)^2 \rangle + 1. \quad (41)$$

In addition, we know the initial value of $v(0) = 0$. By induction it follows that the second moment is

$$\langle v(T)^2 \rangle = T \quad (42)$$

and, since the first moment is zero, the variance is

$$\text{var}(v(T)) = T. \quad (43)$$

The standard deviation – the width of the distribution – of changes in a quantity following a random walk thus scales as the square-root of the number of steps that have been taken, \sqrt{T} . This square-root behaviour leads to many interesting results. It can make averages stable (because \sqrt{T}/T converges to zero for large T), and sums unstable (because \sqrt{T} diverges for large T).

Imagine simulating a single long trajectory of v and plotting it on paper⁴. The amount of time that has to be represented by a fixed length of paper increases linearly with the simulated time because the paper has a finite width to accommodate the horizontal axis. If $\langle \delta v \rangle \neq 0$ then the amount of variation in v that has to be represented by a fixed amount of paper also increases linearly with the simulated time. However, the departures of Δv from its expectation value $T \langle \delta v \rangle$ only increase as the square-root of T . Thus, the amount of paper-space given to these departures scales as $T^{-1/2}$, and for very long simulated times the trajectory will look like a straight line on paper.

In an intermediate regime, fluctuations will still be visible but they will also be approximately Gaussian distributed. In this regime it is often easier to replace the random walk model with the corresponding continuous process.

³The argument is nicely illustrated in [?, Volume 1, Chapter 6-4], where we first came across it.

⁴This argument is inspired by a colloquium presented by Wendelin Werner in the mathematics department of Imperial College London in January 2012. Werner started the colloquium with a slide that showed a straight horizontal line and asked: what is this? Then answered that it was the trajectory of a random walk, with the vertical and horizontal axes scaled equally.

That process is called **Brownian Motion (BM)** and is intuitively thought of as the limit of a random walk where we shorten the duration of a step $\delta t \rightarrow 0$, and scale the width of an individual step so as to maintain the random-walk scaling of the variance, meaning $|\delta v| = \sqrt{\delta t}$. In the limit $\delta t \rightarrow 0$, this implies that $\frac{\delta v}{\delta t}$ diverges, so **BM** trajectories are infinitely jagged, or – in mathematical terms – they are not differentiable. However, the way in which they become non-differentiable, though the $\sqrt{\delta t}$ factor, leaves the trajectories just continuous (this isn't the case for $|\delta v| = \delta t^\alpha$, where α is less than 0.5). Continuity of v means that it is possible to make the difference $|v(t) - v(t + \epsilon)|$ arbitrarily small by choosing ϵ sufficiently small. This would not be possible if there was a jump in $v(t)$, so continuity roughly means that there are no jumps. These subtleties make **BM** a topic of great mathematical interest, and many books have been written about it. We will pick from these books only what is immediately useful to us. To convey the universality of **BM** we define it formally as follows:

DEFINITION: Brownian motion i

If a stochastic process has continuous paths, stationary independent increments, and is distributed according to $\mathcal{N}(\mu t, \sigma^2 t)$ then it is a Brownian motion.

The process can be defined in different ways. Another illuminating definition is this:

DEFINITION: Brownian motion ii

If a stochastic process is continuous, with stationary independent increments, then the process is a Brownian motion.

We quote from [?]: “*This beautiful theorem shows that Brownian motion can actually be defined by stationary independent increments and path continuity alone, with normality following as a consequence of these assumptions. This may do more than any other characterization to explain the significance of Brownian motion for probabilistic modeling.*”

Indeed, **BM** is not just a mathematically rich model but also – due to its emergence through the Gaussian central limit theorem – a model that represents a large universality class, *i.e.* it is a good description of what happens over long times in many other models. **BM** is a process with two parameters, μ and σ . It can be written as a stochastic differential equation

$$dv = \mu dt + \sigma dW \quad (44)$$

where dW is a Wiener increment. The Wiener increment can be defined by its distribution and correlator,

$$dW \sim \mathcal{N}(0, dt) \quad (45)$$

$$\langle dW(t)dW(t') \rangle = dt \delta(t, t'), \quad (46)$$

where $\delta(t, t')$ is the Kronecker delta – zero if its two arguments differ ($t \neq t'$), and one if they are identical ($t = t'$).⁵ The notation $\sim \mathcal{N}(0, dt)$ is short-hand

⁵Physicists often write $dW = \eta dt$, where $\langle \eta \rangle = 0$ and $\langle \eta(t)\eta(t') \rangle = \delta(t - t')$, in which

for “is Gaussian distributed, with mean 0 and variance μt .” In simulations **BM** paths can be constructed from a discretized version of (Eq. 44)

$$v(t + \delta t) = v(t) + \mu \delta t + \sigma \sqrt{\delta t} \xi_t, \quad (47)$$

where ξ_t are instances of a standard normal distribution.

BM itself is not a time-independent random variable – it is a non-ergodic stochastic process. This is easily seen by comparing expectation value and time average

$$\langle v \rangle_N \sim \mu t + \mathcal{N}(0, t/N) \quad (48)$$

$$\bar{v}_t \sim \mu t/2 + \sigma \mathcal{N}(0, t/3) \quad (49)$$

The expectation value, *i.e.* the limit $N \rightarrow \infty$ of (Eq. 7), converges to μt with probability one, so it depends on time, and it’s unclear how to compare that to a time average (which cannot depend on time). Its limit $t \rightarrow \infty$ does not exist.

The time average, the limit $t \rightarrow \infty$ of (Eq. 49) diverges unless $\mu = 0$, but even with $\mu = 0$ the limit is a random variable with diverging variance – something whose density is zero everywhere. In no meaningful sense do the two expressions converge to the same scalar in the relevant limits.

Clearly, **BM**, whose increments are independent instances of a time-independent random variable, is not ergodic. That doesn’t make it unmanageable or unpredictable – we know the distribution of **BM** at any moment in time. But the non-ergodicity has surprising consequences of which we mention one now. We already mentioned that if we plot a Brownian trajectory on a piece of paper it will turn into a straight line for long enough simulation times. This suggests that the randomness of a Brownian trajectory becomes irrelevant under a very natural rescaling. Inspired by this insight let’s hazard a guess as to what the time-average of zero-drift **BM** might be. The simplest form of zero-drift **BM** starts at zero, $v(0) = 0$ and has variance $\text{var}(v(t)) = t$ (this process is also known as the Wiener process). The process is known to be recurrent – it returns to zero, arbitrarily many times, with probability one in the long-time limit. We would not be mad to guess that the time average of zero-drift **BM**,

$$\bar{v} = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t dt' v(t'), \quad (50)$$

will converge to zero with probability one. But we would be wrong. Yes, the process has no drift, and yes it returns to zero infinitely many times, but its time average is not a delta function at zero. It is, instead normally distributed with infinite variance according to the following limit

$$\bar{v} \sim \lim_{t \rightarrow \infty} \mathcal{N}(0, t/3). \quad (51)$$

Averaging over time, in this case, does not remove the randomness. A sample trajectory of the finite-time average is shown in Fig. 8. In the literature the process $\frac{1}{t} \int_0^t dt' v(t')$ is known as the “random acceleration process” [?].

case $\delta(t - t')$ is the Dirac delta function, defined by the integral $\int_{-\infty}^{\infty} f(t) \delta(t - t') dt = f(t')$. Because of its singular nature ($f(t)$ does not exist (“is infinite”), only its integral exists) it can be difficult to develop an intuition for this object, and we prefer the dW notation.

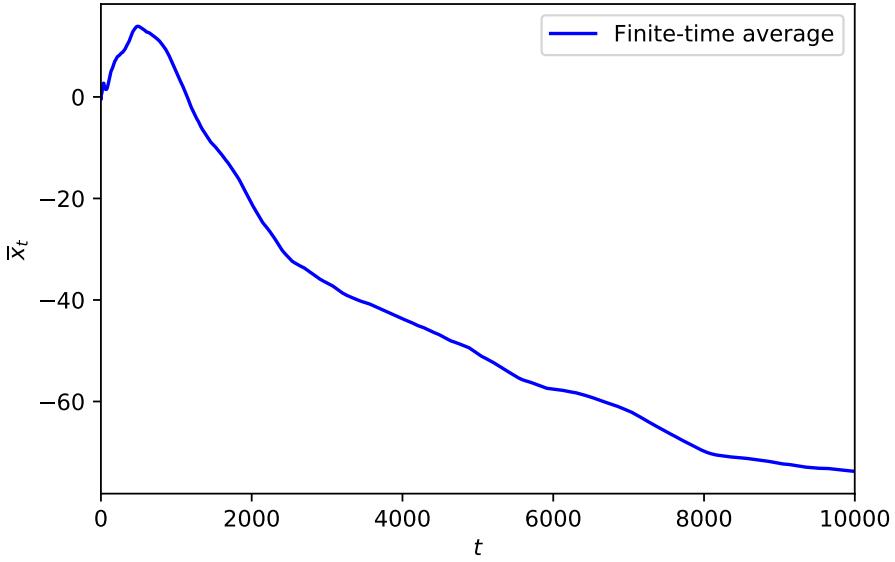


Figure 8: Trajectory of the finite-time average of a zero-drift BM. The process is not ergodic: the time average does not converge to a number, but is instead distributed according to $\mathcal{N}(0, t/3)$ for all times, while the expectation value is zero. It is the result of integrating a BM; integration is a smoothing operation, and as a consequence the trajectories are smoother than BM (unlike a BM trajectory, they are differentiable).

1.4 Geometric Brownian motion

DEFINITION: Geometric Brownian motion

If the logarithm of a quantity performs Brownian motion, the quantity itself performs “geometric Brownian motion.”

While in Sec. 1.3 $v(x) = \ln(x)$ performed BM, x itself performed **Geometric Brownian motion (GBM)**. The change of variable from x to $v(x) = \ln(x)$ is trivial in a sense but it has interesting consequences. It implies, for instance, that

- $x(t)$ is log-normally distributed
- increments in x are neither stationary nor independent
- $x(t)$ cannot become negative
- the most likely value of x (the mode) does not coincide with the expectation value of x .

These and other properties of the log-normal distribution will be discussed in detail in Sec. 3.1.1. The log-normal distribution is not symmetric, unlike the Gaussian distribution.

Again, it is informative to write GBM as a stochastic differential equation.

$$dx = x(\mu dt + \sigma dW). \quad (52)$$

Trajectories for **GBM** can be simulated using the discretized form

$$\delta x = x(\mu\delta t + \sigma\sqrt{\delta t}\xi_t), \quad (53)$$

where $\xi_t \sim \mathcal{N}(0, 1)$ are instances of a standard normal variable. In such simulations we must pay attention that the discretization does not lead to negative values of x . This happens if the expression in brackets in (Eq. 53) is smaller than -1 (in which case x changes negatively by more than itself). To avoid negative values we must have $\mu\delta t + \sigma\sqrt{\delta t}\xi_t > -1$, or $\xi_t < \frac{1+\mu\delta t}{\sigma\sqrt{\delta t}}$. As δt becomes large it becomes more likely for ξ_t to exceed this value, in which case the simulation fails. But ξ_t is Gaussian distributed, meaning it has thin tails, and choosing a sufficiently small value of δt makes these failures essentially impossible.

On logarithmic vertical scales, **GBM** looks like **BM**, and we've already seen some examples. But it is useful to look at a trajectory of **GBM** on linear scales to develop an intuition for this important process.

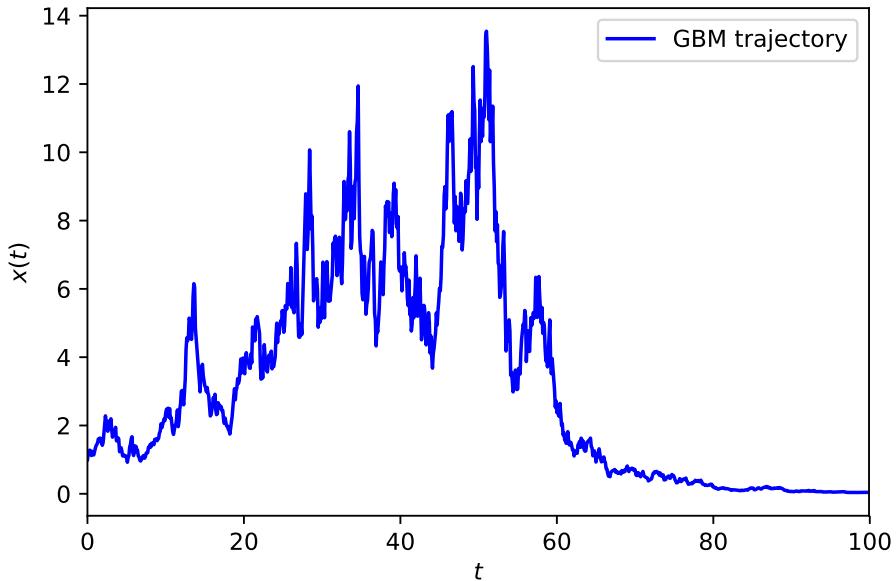


Figure 9: Trajectory of a **GBM**. What happens to the trajectory tomorrow depends strongly on where it is today – for instance, unlike for **BM**, it is difficult to recover from a low value of x , and trajectories are likely to get stuck near zero. Occasional excursions are characterised by large fluctuations. Parameters are $\mu = 0.05$ per time unit and $\sigma = \sqrt{2\mu}$, corresponding to zero growth rate in the long run. It would be easy to invent a story to go with this (completely random) trajectory – perhaps something like “things were going well in the beginning but then a massive crash occurred that destroyed morale.”

The basic message of the game from Sec. 1.1 is that we may obtain different values for growth rates, depending on how we average – an expectation value is one average, a time average is quite another. The game itself is sometimes called the multiplicative binomial process [?], we thank S. Redner for pointing this out to us. **GBM** is the continuous version of the multiplicative binomial

process, and it shares the basic feature of a difference between the growth rate of the expectation value and time-average growth.

The expectation value is easily computed – the process is not ergodic, but that does not mean we cannot compute its expectation value. We simply take the expectations values of both sides of (Eq. 52) to get

$$\langle \text{d}x \rangle = \langle x(\mu dt + \sigma dW) \rangle \quad (54)$$

$$= d \langle x \rangle = \langle x \rangle \mu dt. \quad (55)$$

This differential equation has the solution

$$\langle x(t) \rangle = x(t_0) \exp(\mu t), \quad (56)$$

which determines the growth rate of the expectation value as

$$g_{\langle \rangle} = \mu. \quad (57)$$

As we know, this growth rate is different from the growth rate that materializes with probability 1 in the long run. Computing the time-average growth rate is only slightly more complicated. We will follow this plan: consider the discrete process (Eq. 53) and compute the changes in the logarithm of x , then we will let δt become infinitesimal and arrive at the result for the continuous process. We know $\delta \ln(x(t))$ to be ergodic and reflective of performance over time, therefore we will proceed to take its expectation value to compute the time average of the exponential growth rate of the process.

The change in the logarithm of x in a time interval δt is

$$\ln x(t + \delta t) - \ln x(t) = \ln[x(1 + \mu\delta t + \sigma\sqrt{\delta t}\xi_t)] - \ln x(t) \quad (58)$$

$$= \ln x + \ln(1 + \mu\delta t + \sigma\sqrt{\delta t}\xi_t) - \ln x(t) \quad (59)$$

$$= \ln(1 + \mu\delta t + \sigma\sqrt{\delta t}\xi_t), \quad (60)$$

which we Taylor-expand as $\ln(1 + \text{something small})$ because we will let δt become small. Expanding to second order,

$$\ln x(t + \delta t) - \ln x(t) = \mu\delta t + \sigma\sqrt{\delta t}\xi_t - \frac{1}{2}(\mu\sigma\delta t^{3/2}\xi_t^2 + \sigma^2\delta t\xi_t^2) + o(\delta t^2), \quad (61)$$

using “little-o notation” to denote terms that are of order δt^2 or smaller. Finally, because $\delta \ln x(t)$ is ergodic, by taking the expectation value of this equation we find the time average of $\delta \ln x(t)$

$$\langle \ln x(t + \delta t) - \ln x(t) \rangle = \mu\delta t - \frac{1}{2}(\mu^2\delta t^2 + \sigma^2\delta t) + o(\delta t^2). \quad (62)$$

Letting δt become infinitesimal the higher-order terms in δt vanish, and we find

$$\langle \ln x(t + dt) - \ln x(t) \rangle = \mu dt - \frac{1}{2}\sigma^2 dt, \quad (63)$$

so that the time-average growth rate is

$$\bar{g} = \frac{d \langle \ln x \rangle}{dt} = \mu - \frac{1}{2}\sigma^2. \quad (64)$$

We could have guessed the result by combining Whitworth's argument on the disadvantage of gambling with the scaling of **BM**. Let's re-write the factor $1 - \epsilon$ in (Eq. 24) as $1 - \sigma\sqrt{\delta t}$. According to the scaling of the variance in a random walk, (Eq. 43), this would be a good coarse-graining of some faster process (with shorter time step) underlying Whitworth's game. To find out what happens over one single time step we take the square root of (Eq. 24),

$$[(1 + \sigma\sqrt{\delta t})(1 - \sigma\sqrt{\delta t})]^{1/2} = [1 - \sigma^2\delta t]^{1/2}. \quad (65)$$

Letting δt become infinitesimally small, we replace δt by dt , and the first-order term of a Taylor-expansion becomes exact,

$$[(1 + \sigma\sqrt{\delta t})(1 - \sigma\sqrt{\delta t})]^{1/2} \rightarrow 1 - \frac{\sigma^2}{2}dt, \quad (66)$$

in agreement with (Eq. 64) if the drift term $\mu = 0$, as assumed by Whitworth.

1.4.1 Itô calculus

We have chosen to work with the discrete process here and have arrived at a result that is more commonly shown using Itô's formula. We will not discuss Itô calculus in depth but we will use some of its results. The key insight of Itô was that the non-differentiability of so-called Itô processes leads to a new form of calculus, where in particular the chain rule of ordinary calculus is replaced. An Itô process is a **Stochastic differential equation (SDE)** of the following form

$$dx = a(x, t)dt + b(x, t)dW. \quad (67)$$

If we are interested in the behaviour of some other quantity that is a function of x , let's say $v(x)$, then Itô's formula tells us how to derive the relevant **SDE** as follows:

$$dv = \left(\frac{\partial v}{\partial t} + a(x, t) \frac{\partial v}{\partial x} + \frac{b(x, t)^2}{2} \frac{\partial^2 v}{\partial x^2} \right) dt + b(x, t) \frac{\partial v}{\partial x} dW. \quad (68)$$

Derivations of this formula can be found on Wikipedia. Intuitive derivations, such as [?], use the scaling of the variance, (Eq. 43), and more formal derivations, along the lines of [?], rely on integrals. We simply accept (Eq. 68) as given. It makes it very easy to re-derive (Eq. 64), which we leave as an exercise: use (Eq. 68) to find the **SDE** for $\ln(x)$, take its expectation value and differentiate with respect to t . We will use (Eq. 68) in Sec. 3.1.5. The above computations are intended to give the reader intuitive confidence that Itô calculus can be trusted⁶. We find that, though phrased in different words, our key insight – that the growth rate of the expectation value is not the time-average growth rate – has appeared in the literature not only in 1870 but also in 1944. And in 1956 [?], and in 1966 [?], and in 1991 [?], and at many other times. Yet the depth of this insight remained unprobed.

⁶Itô calculus is one way of interpreting the non-differentiability of dW . Another interpretation is due to Stratonovich, which is not strictly equivalent. However, the key property of **GBM** that we make extensive use of is the difference between the growth rate of the expectation value, $\langle g \rangle$, and the time-average growth rate, \bar{g} . This difference is the same in the Stratonovich and the Itô interpretation, and all our results hold in both cases.

Equation (64), which agrees with Itô calculus, may be surprising. Consider the case of no noise $dx = x\mu dt$. Here we can identify $\mu = \frac{1}{x} \frac{dx}{dt}$ as the infinitesimal increment in the logarithm, $\frac{d \ln(x)}{dt}$, using the chain rule of ordinary calculus. A naïve application of the chain rule to (Eq. 52) would therefore also yield $\frac{d\langle \ln(x) \rangle}{dx} = \mu$, but the fluctuations in GBM have a non-linear effect, and it turns out that the usual chain rule does not apply. Itô calculus is a modified chain rule, (Eq. 68), which leads to the difference $-\frac{\sigma^2}{2}$ between the expectation-value growth rate and the time-average growth rate.

This difference is sometimes called the “spurious drift”, but at the [London Mathematical Laboratory \(LML\)](#) we call it the “Weltschmerz” because it is the difference between the many worlds of our dreams and fantasies, and the one cruel reality that the passage of time imposes on us.

2 Decision theory

Decision theory is a cornerstone of formal economics. As the name suggests, it models how people make decisions. In this chapter we will generalise and formalise the treatment of the coin tossing game to introduce our approach to decision theory. Our central axiom will be that people attempt to maximize the rate at which wealth grows when averaged over time. This is a surprisingly powerful idea. In many cases it eliminates the need for well established but epistemologically troublesome techniques, such as utility functions.

2.1 Models and science fiction

We will do decision theory by using mathematical models, and since this can be done in many ways we will be explicit about how we choose to do it. We will define a gamble, which is a mathematical object, and we will define a decision criterion. The gamble will be reminiscent of real-world situations; and the decision criterion may or may not be reminiscent of how real people make decisions. We will not worry too much about the accuracy of these reminiscences. Instead we will “shut up and calculate” – we will let the mathematical model create its world. Writing down a mathematical model is like laying out the premise for a science-fiction novel. We may decide that people can download their consciousness onto a computer, that medicine has advanced to eliminate ageing and death – these are premises we are at liberty to invent. Once we have written them down we begin to explore the world that results from those premises. A choice of decision criterion implies an endless list of behaviors that will be observed. For example, some criteria will lead to cooperation, others will not, some will lead to the existence of insurance contracts, others will not *etc.* We will explore the worlds created by the different models. Once we have done so we invite you to judge which model you find most useful for your understanding of the world. Of course, having spent many years thinking about these issues we have come to our own conclusions, and we will put them forward because we believe them to be helpful.

To keep the discussion to a manageable volume we will only consider the gamble problem. This is reminiscent of making decisions in an uncertain context – where we have to decide on a course of action now although we don’t know with certainty what will happen to us under any of our choices. To limit the debate even further, we will only consider a setup that corresponds to making purely financial decisions. We may bet on a horse or take out personal liability insurance. This chapter will not tell you whom you should marry or even whose economics lectures you should attend.

2.2 Gambles

One fundamental building block of mathematical decision theory is the gamble. This is a mathematical object that resembles a number of situations in real life, namely situations where we face a decision whose consequences will be purely financial and are somewhat uncertain when we make the decision. A real-world example would be buying a lottery ticket. We define the gamble mathematically as follows.

DEFINITION: Gamble

A gamble is a pair of a random variable, Q , and a duration, δt .

Q is called the payout and takes one of K (mutually exclusive) possible monetary values, $\{q_1, \dots, q_K\}$, associated with probabilities, $\{p_1, \dots, p_K\}$, where $\sum_{j=1}^K p_j = 1$. Payouts can be positive, associated with a monetary gain, or negative, associated with a loss. We order them such that $q_1 < \dots < q_K$.

Everything we need to know about the gamble is contained in the payouts, probabilities, and duration. We relate it to reality through a few examples:

Example: Betting on a fair coin

Imagine betting \$10 on the toss of a fair coin. We would model this with the following payouts and probabilities:

$$q_1 = -\$10, \quad p_1 = 1/2; \quad (69)$$

$$q_2 = +\$10, \quad p_2 = 1/2. \quad (70)$$

The duration would be the time between two coin tosses. If you participate in coin tosses once a week it would be $\delta t = 1$ week.

Example: Playing the lottery

We can also imagine a gamble akin to a lottery, where we pay an amount, F , for a ticket which will win the jackpot, J , with probability, p . The corresponding payouts and probabilities are:

$$q_1 = -F, \quad p_1 = 1 - p; \quad (71)$$

$$q_2 = J - F, \quad p_2 = p. \quad (72)$$

Note that we deduct the ticket price, F , in the payout q_2 . The duration may be $\delta t = 1$ week.

Example: Betting at fixed odds

A bet placed at fixed odds, for example on a horse race can also be modelled as a gamble. Suppose we bet on the horse *Ito* to win the 2015 Prix de l'Arc de Triomphe in Paris at odds of 50/1 (the best available odds on 20th September 2015). *Ito* will win the race with unknown probability, p . If we bet F , then this is modelled by payouts and probabilities:

$$q_1 = -F, \quad p_1 = 1 - p; \quad (73)$$

$$q_2 = 50F, \quad p_2 = p. \quad (74)$$

The duration may be something like $\delta t = 30$ minutes.

Example: The null gamble

It is useful to introduce the null gamble, in which a payout of zero is received with certainty: $q_1 = \$0$, $p_1 = 1$. This represents the ‘no bet’ or ‘do nothing’ option. The duration, δt , has to be chosen appropriately. The meaning of the duration will become clearer later on – often it is the time between two successive rounds of a gamble.

The gamble is a simple but versatile mathematical model of an uncertain future. It can be used to model not only traditional wagers, such as sports bets and lotteries, but also a wide range of economic activities, such as stock market investments, insurance contracts, derivatives, and so on. The gamble we have presented is discrete, in that the payout, Q , is a random variable with a

countable (and, we usually assume, small) number of possible values. The extension to continuous random variables is natural and used frequently to model real-world scenarios where the number of possible outcomes, *e.g.* the change in a stock price over one day, is large.

Suppose now that you have to choose between two options that you've modeled as two gambles (possibly including the null gamble). Which should you choose, and why? This is the gamble problem, the central question of decision theory, and the basis for much of mainstream economics.

2.3 Repetition and wealth evolution

To solve the gamble problem we must propose a criterion to choose between two gambles. Different criteria will result in different decisions – by writing down a criterion we build a model world of model humans who behave in ways that may seem sensible to us or crazy – if the behavior seems crazy we have probably not chosen a good criterion and we should try a different one.

The wealth process $x(t)$ is connected to the gambles our model humans choose to play. Precisely *how* it is affected remains to be specified.

Considering a single round of a gamble in isolation – the so-called ‘one-shot game’ of game theory – is relatively uninstructive in this regard. All we know is that one of the possible payouts will be received, leading to the random value $x(t + \delta t) = x(t) + q$. We don’t yet know how accepting this gamble will affect how our wealth, $x(t)$, grows or decays over time, since one time step isn’t enough for this to become apparent. The one-shot game takes one random value, q , and turns it trivially into another, $x(t) + q$. Time has no significance in a one-shot game. An amount δt elapses, but this could be a single heartbeat or the lifetime of the universe, for all the difference it makes to the analysis.

To establish how your wealth evolves, we must imagine that the world does not come to a grinding halt after the gamble. Instead we imagine that the gamble is repeated over many rounds.⁷ This does not mean that we actually believe that a real-world situation will repeat itself over and over again, *e.g.* we don’t believe that we will bet on the horse *Ito* at odds 50/1 many times in a row. Instead, imagining repetition is a methodological device that allows us to extract tendencies where they would otherwise be invisible. It is the model analogue of the idea that individuals live in time and that their decisions have consequences which unfold over time.

Crucially, *the mode of repetition is not specified in the gamble itself*. It is a second component of the model, which must be specified separately. Initially we shall focus on two modes: *additive* and *multiplicative* repetition. Other dynamics will be considered later on, in Sec. 2.7.

⁷In fact, to make the problem tractable mathematically, it will be necessary to imagine the gamble is repeated indefinitely.

DEFINITION: Additive repetition

If a gamble is repeated additively then a newly generated realization of the random payout, q , is added to $x(t)$ at each round. We define the change in wealth occurring over a single round as

$$\delta x(t) \equiv x(t + \delta t) - x(t). \quad (75)$$

In the additive case, we have

$$\delta x(t) = q. \quad (76)$$

In other words, under additive repetition, δx is a stationary random variable. Starting at time, t_0 , wealth after T rounds is

$$x(t_0 + T\delta t) = x(t_0) + \sum_{\tau=1}^T q(\tau), \quad (77)$$

where $q(\tau)$ is the realisation of the random variable in round τ . This is an evolution equation for wealth following a noisy additive dynamic. Note that $x(t_0 + T\delta t)$ is itself a random variable.

Example: Additive repetition

We return to our first example of a gamble: a \$10 bet on a coin toss. Under additive repetition, successive bets will always be \$10, regardless of how rich or poor you become. Suppose your starting wealth is $x(t_0) = \$100$. Then, following (Eq. 77), your wealth after T rounds will be

$$x(t_0 + T\delta t) = \$100 + \$10k - \$10(T - k) \quad (78)$$

$$= \$[100 + 10(2k - T)], \quad (79)$$

where $0 \leq k \leq T$ is the number of tosses you've won. Note that we have assumed your wealth is allowed to go negative. If not, then the process would stop when $x < \$10$, since you would be unable to place the next \$10 bet.

An alternative is multiplicative repetition. In the example above, let us imagine that the first \$10 bet were viewed not as a bet of fixed monetary size, but as a fixed fraction of the starting wealth (\$100). Under multiplicative repetition, each successive bet is for the same fraction of wealth which, in general, will be a different monetary amount.

The formalism is as follows. The payout, q_j , in the first round is expressed instead as a random wealth multiplier,

$$r_j \equiv \frac{x(t_0) + q_j}{x(t_0)}. \quad (80)$$

The multiplier is another random variable – it also (trivially) defines a stochastic process that is a new instance of the random variable at each point in time, $r(t)$.

The gamble is repeated by applying another instance of the same multiplier at all subsequent rounds:

$$x(t + \delta t) = rx(t). \quad (81)$$

From (Eq. 80) we see that $r(t)$ is a sequence of instances of a random variable with time-independent distribution, since it depends only on Q , which is time-independent, and the starting wealth, $x(t_0)$, which is fixed. However, distributions of successive changes in wealth,

$$\delta x(t) = (r - 1)x(t), \quad (82)$$

are not time-independent, as they depend on t through $x(t)$. The wealth after T rounds of the gamble is

$$x(t_0 + T\delta t) = x(t_0) \prod_{\tau=1}^T r(\tau), \quad (83)$$

where $r(\tau)$ is the realisation of the random multiplier in round τ .

Example: Multiplicative repetition

The \$10 bet on a coin toss is now re-expressed as a bet of a fixed fraction of wealth at the start of each round. Following (Eq. 80), the random multiplier, r , has two possible outcomes:

$$r_1 = \frac{\$100 - \$10}{\$100} = 0.9, \quad p_1 = 1/2; \quad (84)$$

$$r_2 = \frac{\$100 + \$10}{\$100} = 1.1, \quad p_2 = 1/2. \quad (85)$$

The wealth after T rounds is, therefore,

$$x(t_0 + T\delta t) = \$100 (1.1)^k (0.9)^{T-k}, \quad (86)$$

where $0 \leq k \leq T$ is the number of winning tosses. In this example there is no need to invoke a ‘no bankruptcy’ condition, since our individual can lose no more than 10% of his wealth in each round.

The difference between the two modes of repetition might easily be mistaken for a matter of taste. When the \$10 bet was first offered, what difference does it make whether our individual imagined this to be a bet of a fixed size or of a fixed fraction of his wealth? However, the consequences of this choice between imagined situations are enormous. As we saw in the previous lecture, additive and multiplicative dynamics differ as starkly as the linear and exponential functions, and there is evidence that people adjust their behavior to the type of repetition they face. It matters, therefore, that we consider carefully the economic situation we wish to model in order to choose the most realistic mode of repetition. For example, fluctuations in the price of a stock tend to be proportional to the price, *cf.* (Eq. 82), so multiplicativity is the appropriate paradigm here.

Now that we’ve established how the gamble is related to $x(t)$ we can begin to think about decision criteria. Not surprisingly, appropriate growth rates are

useful decision criteria – “pick the gamble that will lead your wealth to grow the fastest” is generally good advice. To be able to follow this advice we will think again about growth rates.

2.4 Growth rates

In the previous lecture we introduced the concept of a growth rate, g , which is the rate of change of a monotonically increasing function of wealth, $v(x(t))$:

$$g(t, \Delta t) \equiv \frac{\Delta v(x(t))}{\Delta t}. \quad (87)$$

The function, v , is chosen such that the increments, $\Delta v(x(t))$, over the period Δt ⁸ are independent instances of a random variable. The growth rate is, therefore, ergodic⁹. We consider g a function of t only inasmuch as this labels a particular realisation of the randomness at a particular point in time.

The statistical irrelevance of the time of measurement is important because we want the distribution of the random growth rate to convey robust information about the underlying process, rather than mere happenstance about when it was sampled.

Under additive repetition, we know from (Eq. 76) that Δx is already ergodic, so we know immediately that the correct mapping is the identity: $v(x) = x$.¹⁰ The ergodic growth rate for an additive process (denoted by the subscript ‘a’) is therefore:

$$g_a(t, \Delta t) = \frac{\Delta x(t)}{\Delta t}. \quad (88)$$

For a multiplicative dynamic, however, using Δx in the numerator of the rate will not do, as we know from (Eq. 82) that changes in $x(t)$ depend on $x(t)$. Instead we must find the mapping $v(x)$ whose increments are independent instances of a random variable. The correct mapping now is the logarithm, since the increment over a single round is

$$\delta \ln x(t) = \ln x(t) - \ln x(t - \delta t) \quad (89)$$

$$= \ln r(t)x(t - \delta t) - \ln x(t - \delta t) \quad (90)$$

$$= \ln r(t), \quad (91)$$

where (Eq. 80) has been used in the second line. This inherits its ergodicity from r . Thus the appropriate growth rate for a multiplicative process (denoted by the subscript ‘m’) over an arbitrary time period is

$$g_m(t, \Delta t) = \frac{\Delta \ln x(t)}{\Delta t}. \quad (92)$$

The distribution of the random variable $g(t, \Delta t)$ does not depend on t but it does depend on Δt . Subject to certain conditions on $\Delta v(x(t))$, the distribution

⁸Note that we use a general time period, Δt , here and not the period of the gamble, δt .

⁹The increments don’t necessarily need to be independent, and examples can be constructed where they are drawn from different distributions at different times, but in our case we have independence and a fixed distribution, and that’s a sufficient condition for the growth rate to be ergodic.

¹⁰In fact, any linear function $v(x) = \alpha x + \beta$ has stationary increments and is monotonically increasing provided $\alpha > 0$. However, there is nothing gained by choosing anything other than $v(x) = x$.

of $g(t, \Delta t)$ narrows as Δt increases, converging to a scalar (just a number, no longer a random variable) in the limit $\Delta t \rightarrow \infty$. In other words, as the effect of the gamble manifests itself over an increasingly long time, the noise is eliminated to reveal a growth rate reflecting the gamble's underlying tendency.

We define this time-average growth rate, \bar{g} , as

$$\bar{g} \equiv \lim_{\Delta t \rightarrow \infty} \{g(t, \Delta t)\}. \quad (93)$$

This is the growth rate that an individual will experience almost surely (*i.e.* with probability approaching one) as the number of rounds of the gamble diverges. Indeed, we can express \bar{g} in precisely these terms,

$$\bar{g} = \lim_{T \rightarrow \infty} \left\{ \frac{v(x(t + T\delta t)) - v(x(t)))}{T\delta t} \right\}, \quad (94)$$

where T is the number of rounds. Expanding the numerator as a sum of increments due to individual rounds of the gamble gives

$$\bar{g} = \lim_{T \rightarrow \infty} \left\{ \frac{1}{T} \sum_{\tau=1}^T \frac{\Delta v(x(t + \tau\delta t))}{\delta t} \right\} \quad (95)$$

$$= \lim_{T \rightarrow \infty} \left\{ \frac{1}{T} \sum_{\tau=1}^T g(t + \tau\delta t, \delta t) \right\} \quad (96)$$

$$= \langle g(t, \delta t) \rangle, \quad (97)$$

where the final line follows from the stationarity and independence of the successive per-round growth rates. This is a restatement of the ergodic property of the previous lecture, namely that the time-average growth rate can be expressed equivalently as the long-time limit and as the ensemble average of the properly chosen ergodic growth rate. For additive and multiplicative dynamics, we obtain the following equivalences:

$$\bar{g}_a = \lim_{\Delta t \rightarrow \infty} \left\{ \frac{\Delta x(t)}{\Delta t} \right\} = \left\langle \frac{\Delta x(t)}{\Delta t} \right\rangle; \quad (98)$$

$$\bar{g}_m = \lim_{\Delta t \rightarrow \infty} \left\{ \frac{\Delta \ln x(t)}{\Delta t} \right\} = \left\langle \frac{\Delta \ln x(t)}{\Delta t} \right\rangle. \quad (99)$$

These follow the form of the general expression,

$$\bar{g} = \lim_{\Delta t \rightarrow \infty} \left\{ \frac{\Delta v(x(t))}{\Delta t} \right\} = \left\langle \frac{\Delta v(x(t))}{\Delta t} \right\rangle. \quad (100)$$

The value of Δt in the ensemble averages is immaterial. In calculations, it is often set to the period, δt , of a single round of the gamble.

Where we are interested in the value of \bar{g} , knowing that it is equal to the value of $\langle g \rangle$ may provide a convenient method of calculating it. However, we will attach no special interpretation to the fact that $\langle g \rangle$ is an expectation value. It is simply a quantity whose value happens to coincide with that of the quantity we're interested in, *i.e.* the time-average growth rate.

Let's take a step back and remark more generally on what we have done so far. We started with a high-dimensional mathematical object, namely the

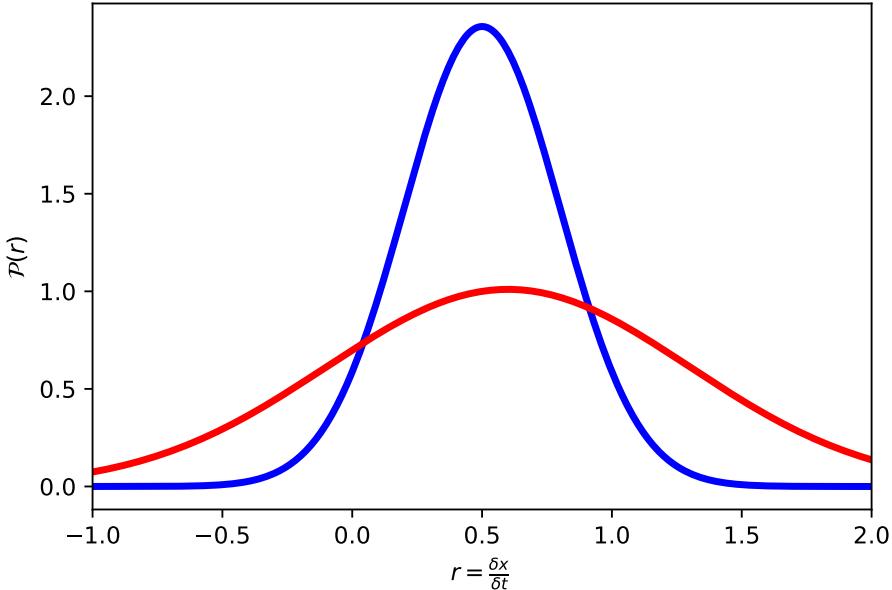


Figure 10: Two possible probability density functions for the per-round multiplier, r , defined in (Eq. 80). The distribution denoted by the blue line has a higher mean and a higher variance than the one in red. How are we to decide which represents the more favourable gamble?

probability distribution of the payout, Q , of the gamble. To this we added two model components: the time period, δt , over which the gamble unfolds; and a dynamic, in essence a set of instructions, specifying how the repeated gamble causes your wealth to evolve. We then collapsed all of this information into a single number, \bar{g} , which characterises the effect of the gamble. The collapse from distribution to single number (or, equivalently, from uncertain to certain quantity) allows different gambles to be compared and, in particular, ranked. This permits an unequivocal decision criterion, which would be much harder to formulate for higher-dimensional objects, such as the two distributions shown in Fig. 10.

2.5 The decision axiom

Our model rationale for deciding between two gambles is simple: given a model for the mode of repetition, choose the gamble with the largest time-average growth rate. In other words, choose the gamble which, if repeated indefinitely, causes your wealth to grow fastest.

We are not saying that real repetitions are necessary. We merely create model humans who base decisions on what would happen to their wealth if they were repeated (infinitely many times). It is a conceptual device – in effect a thought experiment – to elicit the underlying tendency of each gamble. A particular choice that can be represented by gambles may be offered only once and, indeed, in the real world this will often be the case. However, in the real

world it is also the case that a decision is likely to be followed by many others, a scenario to which indefinite repetition is a plausible approximation.

In our thought experiment this decision rule outperforms any other decision rule almost surely: so, at least in that imagined world, the rationale has a logical basis. If our thought experiment is a good approximation to real-world decision scenarios, then our rationale should be a good model of real-world decisions. Certainly it is parsimonious, based on a single, robust quantity and requiring only the gamble and its mode of repetition to be specified. Unlike some treatments of human decision-making, it contains no arbitrary or hard-to-measure psychological factors.

Having said all this, while we think that the decision axiom is reasonable, we stress that it is an *axiom*, *i.e.* something we assert without empirical justification and which is not deduced from more primitive considerations. It defines a model world where certain types of behaviour will be observed. We feel reminded of reality by this model world, but you may disagree or you may prefer a different model that creates a different model world that also reminds you of reality. Other decision axioms are possible and, indeed, have been proposed. For instance, classical decision theory is defined by the axiom that decision makers maximize expected utility.

Our decision rationale can be expressed as a set of instructions. We denote quantities relating to the m^{th} available gamble with the superscript (m) . Each gamble is specified by its random payout, $Q^{(m)}$, and per-round period, $\delta t^{(m)}$.

Growth-optimal decision algorithm

1. Specify $Q^{(m)}$ and $\delta t^{(m)}$ for the gambles offered;
2. Specify the wealth dynamic, *i.e.* the relationship between $\delta x(t)$, $x(t)$, and q ;
3. Find the ergodicity transformation, $v(x)$, of the wealth whose increments are instances of a (time-independent) random variable under this dynamic;
4. Determine the time-average growth rates, $\bar{g}^{(m)}$, either by taking the long-time limit of the growth rates, $g^{(m)}(t, \delta t)$, or by invoking the ergodic property and taking their ensemble averages;
5. Choose the gamble, m , with the largest time-average growth rate.

In examples, we will focus on choices between two gambles, *i.e.* $m \in \{1, 2\}$. Decisions between three or more gambles are straightforward extensions. Often one of the gambles presented is the null gamble, which trivially has a growth rate of zero. In this case, the question then posed is whether the other gamble presented is preferable to doing nothing, *i.e.* bet or no bet?

We will illustrate the decision algorithm by applying it to the coin toss game of the previous lecture. $x(t_0) > \$0$ is the starting wealth and δt is the time between rounds for each of the gambles offered. We recall that the coin toss

gamble is specified by the random payout:

$$q_1^{(1)} = -0.4x(t_0), \quad p_1^{(1)} = 1/2; \quad (101)$$

$$q_2^{(1)} = 0.5x(t_0), \quad p_2^{(1)} = 1/2. \quad (102)$$

Note that, in our setup, the payouts $Q_i^{(m)}$ are always fixed monetary amounts. Here they are expressed as fractions of $x(t_0)$, which is itself a fixed monetary wealth.¹¹ We shall ask our individual to choose between the coin toss and the null gamble,

$$q_1^{(2)} = \$0, \quad p_1^{(2)} = 1. \quad (103)$$

Both the additive and multiplicative versions of the repeated gamble are analysed.

Example: Additive coin toss game

If the repetition is additive, wealth will evolve over T rounds according to:

$$x^{(1)}(t_0 + T\delta t) = x(t_0) + \sum_{\tau=1}^T q^{(1)}(\tau); \quad (104)$$

$$x^{(2)}(t_0 + T\delta t) = x(t_0). \quad (105)$$

Here we have assumed that wealth is free to go negative, *i.e.* that there is no bankrupt state from which the individual can't recover.¹² The ergodicity transformation is the identity, $v(x) = x$, so the growth rates are simply the rates of change of wealth itself. We can express these over the T rounds as:

$$g_a^{(1)}(t) = \frac{x^{(1)}(t + T\delta t) - x(t_0)}{T\delta t} = \frac{1}{T} \sum_{\tau=1}^T \frac{q^{(1)}(\tau)}{\delta t}; \quad (106)$$

$$g_a^{(2)}(t) = \frac{x^{(2)}(t + T\delta t) - x(t_0)}{T\delta t} = \$0 \quad (107)$$

per unit time. The long-time limit of the growth rate for the null gamble is trivially $g_a^{(2)} = \$0$ per unit time. For the coin toss, we calculate it as

$$\bar{g}_a^{(1)} = \lim_{T \rightarrow \infty} \left\{ \frac{1}{T} \sum_{\tau=1}^T \frac{q^{(1)}(\tau)}{\delta t} \right\} \quad (108)$$

$$= \left\langle \frac{q^{(1)}}{\delta t} \right\rangle \quad (109)$$

$$= \frac{p_1^{(1)} q_1^{(1)} + p_2^{(1)} q_2^{(1)}}{\delta t} \quad (110)$$

$$= \frac{0.05x(t_0)}{\delta t}, \quad (111)$$

¹¹Even though this formulation might appear to encode a multiplicative dynamic (largely because it comes from an imagined multiplicative game), we have arranged things so that formally it does not. Indeed, it encodes no dynamic at all: that is specified separately.

which is positive (assuming $x(t_0) > \$0$). Therefore, $\bar{g}_a^{(1)} > \bar{g}_a^{(2)}$ and our individual should accept the coin toss gamble under additive dynamics.

We see from this example that the decision rule under additive repetition is to maximise $\langle q/\delta t \rangle$.¹³ This is the rate of change of the expected wealth, which, as we know from (Eq. 98), happens to coincide under this dynamic with the time-average growth rate. We will see later that humans tend not to act to maximise $\langle q/\delta t \rangle$ in reality. This may not be a great shock: additive repetition without bankruptcy isn't going to win many prizes for the most realistic model of wealth evolution.

Let's try multiplicative repetition instead.

Example: Multiplicative coin toss game

The payout, $Q^{(1)}$, is re-expressed as a per-round multiplier,

$$r^{(1)} = \frac{x(t_0) + q^{(1)}}{x(t_0)}, \quad (112)$$

which takes the values:

$$r_1^{(1)} = \frac{x(t_0) + q_1^{(1)}}{x(t_0)} = 0.6, \quad p_1^{(1)} = 1/2; \quad (113)$$

$$r_2^{(1)} = \frac{x(t_0) + q_2^{(1)}}{x(t_0)} = 1.5, \quad p_2^{(1)} = 1/2. \quad (114)$$

Under multiplicative dynamics, the wealth evolves according to:

$$x^{(1)}(t_0 + T\delta t) = x(t_0) \prod_{\tau=1}^T r^{(1)}(\tau); \quad (115)$$

$$x^{(2)}(t_0 + T\delta t) = x(t_0). \quad (116)$$

The ergodicity transformation is the logarithm, $v(x) = \ln x$. We have already discussed why, but one way of seeing this is to take logarithms of (Eq. 115). This converts the product into a sum of independent instances of a random variable:

$$\ln x^{(1)}(t_0 + T\delta t) = \ln x(t_0) + \sum_{\tau=1}^T \ln r^{(1)}(\tau); \quad (117)$$

$$\ln x^{(2)}(t_0 + T\delta t) = \ln x(t_0). \quad (118)$$

Therefore, $\ln x$ is the desired quantity whose increments inherit their er-

¹²We could model this realistic feature by an absorbing boundary on $x(t)$, if we were so minded.

¹³Too frequently in presentations of decision theory, it is assumed implicitly that δt is the same for all available gambles and the decision algorithm is presented as the maximisation of the expected payout, $\langle q \rangle$. While this is equivalent if all the $\delta t^{(m)}$ are identical, it is not if they aren't. Moreover, the assumption is usually left unstated. This is unhelpful in that it masks the important role of time in the analysis and, in particular, the fact that our individual is maximising a *rate*.

godicity from q . The growth rates, expressed over T rounds, are:

$$g_m^{(1)}(t) = \frac{\ln x^{(1)}(t + T\delta t) - \ln x(t_0)}{T\delta t} = \frac{1}{T} \sum_{\tau=1}^T \frac{\ln r^{(1)}(\tau)}{\delta t}; \quad (119)$$

$$g_m^{(2)}(t) = \frac{\ln x^{(2)}(t + T\delta t) - \ln x(t_0)}{T\delta t} = 0 \quad (120)$$

per unit time. As in the additive case, we take the $T \rightarrow \infty$ limits. For the null gamble this is trivial: $\bar{g}_m^{(2)} = 0$ per unit time. For the coin toss gamble, we get

$$\bar{g}_m^{(1)} = \left\langle \frac{\ln r^{(1)}}{\delta t} \right\rangle = \frac{\ln(\sqrt{0.9})}{\delta t}, \quad (121)$$

which is negative. Thus, $\bar{g}_m^{(1)} < \bar{g}_m^{(2)}$ under multiplicative dynamics and our individual should decline the coin toss. That this is the opposite of his decision under additive repetition highlights the importance of specifying a dynamic that corresponds well to what is happening in reality.

Another way of presenting the repeated coin toss is to express the wealth after T rounds as

$$x^{(1)}(t_0 + T\delta t) = x(t_0) \left(r_T^{(1)} \right)^T, \quad (122)$$

where

$$r_T^{(1)} = (0.6)^{(T-k)/T} (1.5)^{k/T} \quad (123)$$

is the equivalent per-round multiplier after T rounds and $0 \leq k \leq T$ is the number of winning rounds. r_T is a random variable but it converges almost surely to a scalar in the long time limit,

$$r_\infty^{(1)} \equiv \lim_{T \rightarrow \infty} \{r_T^{(1)}\} = (0.6)^{1/2} (1.5)^{1/2} = \sqrt{0.9}, \quad (124)$$

since $k/T \rightarrow 1/2$ as $T \rightarrow \infty$ (the coin is fair). $r_\infty^{(1)} < 1$ so the individual's wealth is sure to decay over time and he should decline the gamble. The two approaches are, of course, linked, in that

$$\bar{g}_m^{(1)} = \frac{\ln r_\infty^{(1)}}{\delta t}. \quad (125)$$

Here we see that our decision rule boils down to maximising

$$\left\langle \frac{\ln r}{\delta t} \right\rangle = \left\langle \frac{\ln(x(t_0) + q) - \ln x(t_0)}{\delta t} \right\rangle. \quad (126)$$

This coincides with the time-average growth rate in (Eq. 99).

2.6 The expected-wealth and expected-utility paradigms

Our decision rule under additive repetition of the gamble is to maximise

$$\left\langle \frac{\delta x}{\delta t} \right\rangle = \left\langle \frac{q}{\delta t} \right\rangle, \quad (127)$$

i.e. the rate of change of the expectation value of wealth. This was, in fact, the first decision rule to be suggested when gamble problems were considered in the early days of probability theory in the 17th century. We will call this the ‘expected-wealth paradigm’. It was not derived as we have derived it, from a criterion to maximise growth over repetition. Instead, it was essentially proposed as the decision axiom itself, with no reference to dynamics. It is easy to see why: it is a simple rule containing a familiar type of average, which incorporates all the possible outcomes of the game. Indeed, it would be logically sound if we could play the game many times in parallel, thereby accessing all the possible outcomes.

In the language of economics, the expected-wealth paradigm treats humans as ‘risk neutral’, *i.e.* they have no preference between gambles whose expected changes in wealth are identical (over a given time interval). This treatment has been known to be a flawed model of human decision-making since at least 1713 [?, p. 402], in that it does not accord well with observed behaviour.

The conventionally offered reason for this predictive failure is that the value to an individual of a possible change in wealth depends on how much wealth he already has and his psychological attitude to taking risks. In other words, people do not treat equal amounts of extra money equally. This makes intuitive sense: an extra \$10 is much less significant to a rich man than to a pauper for whom it represents a full belly; an inveterate gambler has a different attitude to risking \$100 on the spin of a roulette wheel than a prudent saver, their wealths being equal.

In 1738 Daniel Bernoulli [?], after correspondence with Cramer, devised the ‘expected-utility paradigm’ to model these considerations. He observed that money may not translate linearly into usefulness and assigned to an individual an idiosyncratic utility function, $u(x)$, that maps his wealth, x , into usefulness, u . He claimed that this was the true quantity whose rate of change of expected value,

$$\langle r_u \rangle \equiv \left\langle \frac{\delta u(x)}{\delta t} \right\rangle, \quad (128)$$

is maximised in a decision between gambles.

This is the axiom of utility theory. It leads to an alternative decision algorithm, which we summarise here:

Expected-utility decision algorithm

1. Specify $Q^{(m)}$ and $\delta t^{(m)}$ for the gambles offered;
2. Specify the individual's idiosyncratic utility function, $u(x)$, which maps his wealth to his utility;
3. Determine the rate of change of his expected utility over a single round of the gamble (no dynamic is specified so it's unclear how a gamble would be repeated),

$$\langle r_u \rangle^{(m)} = \left\langle \frac{u(x + q^{(m)}) - u(x)}{\delta t^{(m)}} \right\rangle; \quad (129)$$

4. Choose the gamble, m , with the largest $\langle r_u \rangle^{(m)}$.

Despite their conceptually different foundations, we note the similarities between the maximands¹⁴ of our growth-optimal decision theory, (Eq. 100), and the expected-utility paradigm, (Eq. 128). Our decision theory contains a mapping which transforms wealth into a variable, v , whose increments are instances of a time-independent random variable. This mapping depends on the wealth dynamic which describes how the gamble is repeated. The expected-utility paradigm contains a function which transforms wealth into usefulness. This is determined by the idiosyncratic risk preferences of the individual. If we identify the ergodicity transformation of the former with the utility transformation of the latter, then the expressions are the same.

But we caution against the conceptual world of expected utility theory. It uses expectation values, where they are inappropriate (because decisions of an individual are considered, not of many parallel systems), and it corrects for this error by introducing a non-linear mapping of wealth (the utility function) whose specific form cannot be pinned down convincingly. Finally, because of this conceptual weakness, utility theory is poorly defined. The very first paper on the topic contains two contradictory definitions of expected utility theory [?], and over the centuries several others have been added.

Nonetheless, with a few assumptions, expected utility theory as we've presented it above is consistent with growth rate optimisation, provided a suitable pair of dynamic and utility function is used. For multiplicative dynamics, the necessary utility function is the logarithm. That this is the most widely used utility function in both theory and practice is a psychological fluke in the classic mindset; from our perspective it indicates that our brains have evolved to produce growth-optimal decisions in a world governed by multiplicative dynamics, *i.e.* where entities produce more of themselves. Incidentally, a common definition of life is "that which produces more of itself," or as Harold Morowitz put it [?, p. 5] "Living systems self-replicate, that is, they give rise to organisms like themselves." From our perspective, the prevalence of logarithmic utility reflects our evolution in an environment of living things.

Thus we can offer a different reason for the predictive failure of the expected-wealth paradigm. In our framework this corresponds to good decisions under

¹⁴The quantities to be maximised.

additive repetition, which we claim is generally a poor model of how wealth evolves.¹⁵ It fails, therefore, because it corresponds to an unrealistic dynamic.

It's worth being explicit about how our theory differs from expected utility theory. In our model what's stable about human behavior is this: humans optimize wealth over time. Utility theory says humans optimize utility across the ensemble. Given a dynamic, our paradigm predicts human behavior that can be mapped to a predicted utility function. Utility theory believes that behavior, specifically risk preferences, is an idiosyncratic thing: it does not depend on the dynamics but on the individual. This difference (behavior is determined by dynamics vs. behavior is determined by indiosyncrasy) means that in principle we can find out which theory is right. We can change dynamic and see if people change behavior. That would invalidate expected utility theory. We can also take several people and expose them to the same dynamic – the extent to which they display utility functions that are incompatible with the dynamic would invalidate our theory, insofar as it is interpreted to predict human behavior. Our theory provides the optimal behavioral protocol, in terms of long-term wealth growth, but of course real humans will only optimize long-term wealth growth to a certain degree. Nevertheless, we are happy to report that a Danish group of experimentalists has recently carried out experiments where subjects were exposed to different wealth dynamics, to see whether the utility functions implied by their behavior changed as predicted by our theory. At the time of writing, we're still waiting for the results.

2.7 General dynamics

Before we come to example applications of decision theory, it is time to discuss dynamics that are neither additive nor multiplicative and their relation to general utility functions.

2.7.1 Why discuss general dynamics?

What are we trying to achieve with this? First of all, where the time perspective has come up in history, *e.g.* [?, ?], it was always in the context of multiplicative dynamics, which, as we saw in the previous section, corresponds to logarithmic utility. One persistent criticism from people trained to think in terms of utility has been: what if my utility function is not logarithmic? In other words, the time perspective has seemed overly restrictive to many people.

As a matter of epistemology, we want to be somewhat restrictive. Imagine the opposite: a model that can produce absolutely any behavior. Because it can produce anything, it cannot say “the reason this happens and not that is X.” But that's exactly the type of statement we need in order to make sense of the world – why do some structures exist and not others? Consider a specific case of a universal model: the alphabet, including punctuation. That's all the building blocks you need to tell any story you want, true or false, interesting or not. The alphabet is a useful thing, but it's not a good scientific model because it's not restrictive enough. Most sentences allowed by the alphabet are gibberish. Like “flowerbamdoodle zap.”

¹⁵It would correspond, for example, to the interest payments in your bank account being independent of your balance!

Having said this, it is true that we can also err on the other end of the spectrum and have a model that's too restrictive. Imagine, instead of having the alphabet plus punctuation at your disposal you were only allowed to use sentences of five words, beginning with "heteroglot." That would make it difficult to write an insightful account of the lifecycle of newts, for example.

But to return to the topic at hand, one reason for generalizing the dynamics is to answer to the criticism of utility-theory users who dislike the restriction, as they would phrase it, to logarithmic utility functions.

The second reason for generalizing at this point is that we feel there are important aspects of decision-making that cannot be understood with multiplicative dynamics. Here is an example. Under multiplicative dynamics risk aversion is growth optimal. That means your wealth will grow faster over time if you make decisions that are more cautious than decisions you would make to optimize the expectation value of your wealth. But we know that in reality there are many situations where risk seeking (the opposite of risk aversion) will make your wealth grow faster.

It's worth discussing this because it shows an important epistemological difference between utility theory and time optimization. There's a big difference between the following two life situations.

1. My earned income is much more than what I need to live. I'm sure you know the problem: at the end of each month, having paid the rent for my flat share, bought all the books I was curious about and all the surfwax I needed, I'm left with \$50,000 of my \$52,000 monthly paycheck. I'll put that aside for a rainy day, stick it into bitcoin or buy some Enron shares. Having done this for several years, most of my \$50,000,0000 wealth is just riding the stock market.
2. You won't know about this, but here's another scenario: I don't have \$50,000 to put aside at the end of each month. Actually, a week after payday, everything has been spent, and the remaining 3 weeks have to be bridged. I help you move those boxes, and in return you make lunch. Every couple of months I get a new credit card to max out, until they're onto me and cut me off. That's followed by a few years of handing over everything I earn to my creditors, and after that I declare bankruptcy to start another cycle. I have no wealth riding anything.

We will turn these descriptions into mathematics later on, but for now let's analyse them from the dynamic perspective, and then from the perspective of utility theory to bring out the conceptual differences.

Dynamic perspective: From these situations, I can clearly see that there's a difference between the dynamics my wealth will follow. In situation 1) my wealth is roughly a multiplicative process. Earned income is negligible, and investment income dominates. Not so in situation 2), where earned income is the only income I have. It's so low that I have no savings, I can't pay my health insurance, can't buy a car to get a job in the next town, can't pay for university. I'm stuck at the bottom.

In situation 1) I can relax. I'm happy with the status quo, and there's no reason for me to change it. I should be change-averse, which is called risk-averse in the literature. In situation 2) the status quo is terrible, and I should

be change-seeking, or risk-seeking if you prefer that word. It's growth optimal – rational, according to our rationality model – to play the lottery and hope for a big win, even if the expected return is negative. In situation 2, if as little as just \$1,000,000 fell into my lap, my life would change dramatically. Not because I would have all the money I need but because my wealth would enter a different dynamical regime.

Utility perspective: Utility theory would see me in situation 1) and conclude that my utility function is concave. My actions are optimal with respect to my utility function. Where that function comes from is unknown, people will discuss nature vs. nurture, psychology, and brain architecture, something like that. In situation 2) my actions are also optimal with respect to my utility function. It's just that that happens to be convex – I'm the type of person who likes to take risks, again someone will bring up psychology and neuro-imaging. Someone trained to think in terms of expectation values may also conclude that I'm a bit stupid because I accept gambles with negative expected return. Perhaps he (usually it's a he) will perceive the arrow of causality as follows: the reason I'm so poor is that I make such terrible financial decisions (which is, of course, a possibility).

The utility perspective tends to draw our attention on the psychology of the decision maker, whereas the dynamic perspective focuses on the situation of the decision maker.

2.7.2 Technical setup

With dynamics generalized beyond additive and multiplicative we have to be careful not to let the scope of our treatment balloon into meaninglessness. We also have to pick a setup where the mathematics won't lead to pages of equations without actually adding much. Here's what we do: we restrict ourselves to wealth dynamics that are expressed as an Itô process, which you may remember from (Eq. 67) in Sec. 1.4.1. We will further restrict ourselves to coefficient functions $a(\mathbf{x})$ and $b(\mathbf{x})$ without explicit t dependence, meaning wealth will follow

$$d\mathbf{x} = a(\mathbf{x})dt + b(\mathbf{x})dW. \quad (130)$$

We can still choose additive dynamics, namely by setting $a = \mu$ and $b = \sigma$ as constants (Brownian motion, (Eq. 44)). We can also choose multiplicative dynamics, with $a = \mu x$ and $b = \sigma x$ (geometric Brownian motion, (Eq. 52)).

We are interested in wealth – more is better. We can position ourselves, make one choice or another, and then let time act. Choosing between two repeated gambles is thus a choice between two random sequences of wealths, let's call them $\mathbf{x}(t)$ and $\mathbf{x}^*(t)$. If life were very simple we could just look at both of them at some moment in the future, t^* say, and choose the bigger one. But that's generally not possible because of noise – both $\mathbf{x}(t^*)$ and $\mathbf{x}^*(t^*)$ are random variables, and we don't know which realizations we will encounter.

So what do we do? Let's build this up systematically, starting from a probabilistic statement, and let time help us get rid of the randomness later. At each decision time, t_0 , we want to maximise subsequent changes in wealth by selecting $\mathbf{x}(t)$ so that if we wait long enough wealth will be greater under the

chosen process than under the alternative process *with certainty*. Mathematically speaking, there exists a sufficiently large Δt such that the probability of the chosen $x(t)$ being greater than $x^*(t)$ is arbitrarily close to one,

$$\forall \epsilon, x^*(t) \quad \exists \Delta t \quad \text{s.t.} \quad \mathcal{P}(\Delta x > \Delta x^*) > 1 - \epsilon, \quad (131)$$

where $0 < \epsilon < 1$ specifies how certain we want to be. To keep notation simple we've used

$$\Delta x \equiv x(t_0 + \Delta t) - x(t_0); \quad (132)$$

$$\Delta x^* \equiv x^*(t_0 + \Delta t) - x^*(t_0). \quad (133)$$

The criterion is necessarily probabilistic because the quantities Δx and Δx^* are random variables and it's possible for either of them to exceed the other for any finite Δt . Only in the limit $\Delta t \rightarrow \infty$ does the randomness vanish from the system.

Conceptually this criterion is tantamount to maximising $\lim_{\Delta t \rightarrow \infty}\{\Delta x\}$ or, equivalently, $\lim_{\Delta t \rightarrow \infty}\{\Delta x/\Delta t\}$. However, neither limit is guaranteed to exist. For example, consider a choice between two geometric Brownian motions,

$$dx = x(\mu dt + \sigma dW), \quad (134)$$

$$dx^* = x^*(\mu^* dt + \sigma^* dW). \quad (135)$$

Assuming that both grow over time, meaning $\mu > \sigma^2/2$ and $\mu^* > \sigma^{*2}/2$, the quantities $\Delta x/\Delta t$ and $\Delta x^*/\Delta t$ both diverge in the limit $\Delta t \rightarrow \infty$. The growth is exponential, so linear additive changes will diverge over time. A criterion requiring the larger rate of wealth change to be selected fails to yield a decision: comparing ∞ to ∞ is not meaningful.

But what about that idea of transforming wealth? For the moment we're only interested in which wealth will be larger (x or x^*); we don't care by how much. That means we don't have to consider x itself, but any monotonically increasing function of x will also do. Let's again call that $v(x)$. Why do we keep coming back to monotonic functions? Well, monotonicity means that the events $x > x^*$ and $v(x) > v(x^*)$ are identical – whenever one of the inequalities is satisfied, the other is too. So a monotonically increasing function of x works as an indicator and can help us out of that infinity-fix we just found ourselves in. We define:

$$\Delta v \equiv v(x(t_0 + \Delta t)) - v(x(t_0)); \quad (136)$$

$$\Delta v^* \equiv v(x^*(t_0 + \Delta t)) - v(x^*(t_0)). \quad (137)$$

The monotonicity of $v(x)$ means that the events $\Delta x > \Delta x^*$ and $\Delta v > \Delta v^*$ are the same. Taking $\Delta t > 0$ allows this event to be expressed as $\Delta v/\Delta t > \Delta v^*/\Delta t$, whence the decision criterion in (Eq. 131) becomes

$$\forall \epsilon, x^*(t) \quad \exists \Delta t \quad \text{s.t.} \quad \mathcal{P}\left(\frac{\Delta v}{\Delta t} > \frac{\Delta v^*}{\Delta t}\right) > 1 - \epsilon. \quad (138)$$

Our decision criterion has been recast to focus on the rate of change

$$g_a(u) \equiv \frac{\Delta u}{\Delta t}, \quad (139)$$

As before, it is conceptually similar to maximising

$$\overline{g_a} \equiv \lim_{\Delta t \rightarrow \infty} \left\{ \frac{\Delta v(x)}{\Delta t} \right\} = \lim_{\Delta t \rightarrow \infty} \{g_a(v)\}. \quad (140)$$

If $x(t)$ satisfies certain conditions, to be discussed below, then the function $v(x)$ can be chosen such that this limit exists. We shall see that $\overline{g_a}(v(x))$ is then the appropriately defined time-average growth rate of x . This is quite a powerful bit of mathematics: by insisting on the existence of the limit, we force ourselves to choose $v(x)$ in a certain way. That certain way guarantees that the correct form of growth rate is used. For example, if $x(t)$ is Brownian motion, $v(x)$ will be linear, and if it's geometric Brownian motion, $v(x)$ will be logarithmic. This has nothing to do with psychology and behavior, it's simply imposed on us by the dynamics and our wish to compare long-term performances in a mathematically meaningful way. For the moment we leave our criterion in the probabilistic form of (Eq. 138) but to continue the discussion we assume that the limit (Eq. 140) exists.

Let's connect this back to the general relationship between expected utility theory and ergodicity economics. Perhaps (Eq. 140) is the same as the rate of change of the expectation value of Δv

$$\overline{g_a}(v) = \frac{\langle \Delta v \rangle}{\Delta t}. \quad (141)$$

We could then make the identification of $v(x)$ being the utility function $u(x)$, noting that our criterion is equivalent to maximizing the rate of change in expected utility. We note Δv and hence $g_a(v)$ are random variables but $\langle \Delta v \rangle$ and $\overline{g_a}(v)$ are not. Taking the expectation value is one way of removing randomness from the problem, and taking the long-time limit is another. As we saw in Sec. 1.1, (Eq. 7), the expectation value is simply a different limit: it's an average over N realizations of the random number Δv , in the limit $N \rightarrow \infty$. The effect of removing randomness is that the process $x(t)$ is collapsed into the scalar $\langle \Delta v \rangle$, and consistent transitive decisions are possible by ranking the relevant scalars. In general, maximising $\overline{g_a}(v)$ does not yield the same decisions as the criterion espoused in (Eq. 138). This is only the case for a particular function $v(x)$ whose shape depends on the process $x(t)$, *i.e.* on the dynamics. Our aim is to find these pairs of processes and functions. When using such $v(x)$ as the utility function, expected utility theory will be consistent with optimisation over time, so long as no one changes the dynamics. It is then possible to interpret behavior consistent with expected utility theory with utility function $u(x)$ in purely dynamical terms: such behavior will lead to the fastest possible wealth growth over time.

We ask what sort of dynamic v must follow so that $\overline{g_a}(v) = \langle g_a(v) \rangle$ or, put another way, so that $g_a(v)$ is an ergodic observable, in the sense that its time and ensemble averages are the same [?, p. 32].

We start by expressing the change Δv as a sum over M equal time intervals,

$$\Delta v \equiv v(t_0 + \Delta t) - v(t_0) \quad (142)$$

$$= \sum_{m=1}^M [v(t_0 + m\delta t) - v(t_0 + (m-1)\delta t)] \quad (143)$$

$$= \sum_{m=1}^M \delta v_m(t), \quad (144)$$

where $\delta t \equiv \Delta t/M$ and $\delta v_m(t) \equiv v(t_0 + m\delta t) - v(t_0 + (m-1)\delta t)$. From (Eq. 140) we have

$$\overline{g_a} = \lim_{\Delta t \rightarrow \infty} \left\{ \frac{1}{\Delta t} \sum_{m=1}^M \delta v_m \right\} \quad (145)$$

$$= \lim_{M \rightarrow \infty} \left\{ \frac{1}{M} \sum_{m=1}^M \frac{\delta u_m}{\delta t} \right\}, \quad (146)$$

keeping δt fixed. From (Eq. 141) we obtain

$$\langle g_a \rangle = \lim_{N \rightarrow \infty} \left\{ \frac{1}{N} \sum_{n=1}^N \frac{\Delta v_n}{\Delta t} \right\} \quad (147)$$

where each Δv_n is drawn independently from the distribution of Δv .

We now compare the two expressions (Eq. 146) and (Eq. 147). Clearly the value of $\overline{g_a}$ in (Eq. 146) cannot depend on the way in which the diverging time period is partitioned, so the length of interval δt must be arbitrary and can be set to the value of Δt in (Eq. 147), for consistency we then call $\delta v_m(t) = \Delta v_m(t)$. Expressions (Eq. 146) and (Eq. 147) are equivalent if the successive additive increments, $\Delta v_m(t)$, are distributed identically to the Δv_n in (Eq. 147), which requires only that they are independent realizations of a time-independent random variable.

Thus we have a condition on $v(t)$ which suffices to make $\overline{g_a} = \langle g_a \rangle$, namely that it be a stochastic process whose additive increments are independent realizations of a time-independent random variable. This means that $v(t)$ is, in general, a Lévy process. If we restrict our attention to processes with continuous paths, then $v(t)$ must be a Brownian motion with drift, as we learned in Sec. 1.3. We write this as

$$dv = a_v dt + b_v dW. \quad (148)$$

By arguing backwards we can address concerns regarding the existence of $\overline{g_a}$. If v follows the dynamics specified by (Eq. 148), then it is straightforward to show that the limit $\overline{g_a}$ always exists and takes the value a_v . Consequently the decision criterion (Eq. 138) is equivalent to the optimisation of $\overline{g_a}$, the time-average growth rate. The process $x(t)$ may be chosen such that (Eq. 148) does not apply for any choice of $u(x)$. In this case we cannot interpret expected utility theory dynamically, and such processes are likely to be pathological.

This gives our central result.

Equivalency criterion

For expected utility theory to be equivalent to optimisation over time, utility must follow a stochastic process with ergodic additive increments.

This is a fascinating general connection. Provided that $v(x)$ is invertible, *i.e.* provided that its inverse, $x(v)$, exists, a simple application of Itô calculus to (Eq. 148) yields directly the stochastic differential equation obeyed by the wealth, x .

Translating into utility language, every invertible utility function is actually an encoding of a unique wealth dynamic which arises as utility performs a Brownian motion. Curiously, a celebrated but erroneous paper by Karl Menger [?] “proved” that all utility functions must be bounded (the proof is simply wrong). Boundedness makes utility functions non-invertible and precludes the developments we present here. Influential economists lauded Menger’s paper, including Paul Samuelson [?, p. 49] who called it “a modern classic that [...] stands above all criticism.” This is one reason why mainstream economics has failed to use the optimization of wealth growth over time to understand human behavior – a criterion we consider extremely simple and natural. A discussion of Menger’s precise errors can be found in [?, p. 7]. Although mainstream economics still considers boundedness of utility to be formally required, it is such an awkward restriction that John Campbell noted recently [?] that “this requirement is routinely ignored.”

2.7.3 Dynamic from a utility function

We now use the identification of $v = u$ to illustrate the relationship between utility functions and wealth dynamics. For the reasons discussed above we assume that utility follows a Brownian motion with drift.

If $u(x)$ can be inverted to $x(u) = u^{-1}(u)$, and $x(u)$ is twice differentiable, then it is possible to find the dynamic that corresponds to the utility function $u(x)$. Equation (148) is an Itô process. Itô’s lemma tells us that dx will be another Itô process, and Itô’s formula specifies how to find dx in terms of the relevant partial derivatives

$$dx = \underbrace{\left(\frac{\partial x}{\partial t} + a_u \frac{\partial x}{\partial u} + \frac{1}{2} b_u^2 \frac{\partial^2 x}{\partial u^2} \right) dt}_{a_x(x)} + \underbrace{b_u \frac{\partial x}{\partial u} dW}_{b_x(x)} \quad (149)$$

We have thus shown that

Invertible utility functions have dynamic interpretations

For any invertible utility function $u(x)$ a class of corresponding wealth processes dx can be obtained such that the rate of change (*i.e.* the additive growth rate) in the expectation value of net changes in utility is the time-average growth rate of wealth.

The utility function is then, simply, the ergodicity mapping, and optimizing its expected changes is equivalent to optimizing time-average wealth growth for the corresponding wealth process.

The origin of optimizing expected utility can be understood as follows: in the 18th century, when utility theory was introduced, the difference between ergodic and non-ergodic processes was unknown, and all stochastic processes were treated by computing expectation values. Since the expectation value of the wealth process is an irrelevant mathematical object to an individual whose wealth is well modelled by a non-ergodic process the available methods failed. The formalism was saved by introducing a non-linear mapping of wealth, namely the utility function. The (failed) expectation value criterion was interpreted as theoretically optimal, and the non-linear utility functions were interpreted as a psychologically motivated pattern of human behavior. Conceptually, this is wrong.

Optimization of time-average growth recognizes the non-ergodicity of the situation and computes the appropriate object from the outset – a procedure whose building blocks were developed beginning in the late 19th century. It does not assume anything about human psychology and indeed predicts that the same behavior will be observed in any growth-optimizing entities that need not be human.

Equation (149), creates pairs of utility functions $u(x)$ and dynamics dx . In Sec. 2.4 we saw in a discrete setting that the ergodicity mapping for additive wealth dynamics is the identity function, and for multiplicative dynamics it is the logarithm. Interpreting utility functions as ergodicity mappings, we can summarize this in continuous time as follows.

- The linear utility function corresponds to additive wealth dynamics (Brownian motion),

$$u(x) = x \quad \leftrightarrow \quad dx = a_u dt + b_u dW, \quad (150)$$

as is easily verified by substituting $x(u) = u$ in (Eq. 149).

- The logarithmic utility function corresponds to multiplicative wealth dynamics (geometric Brownian motion),

$$u(x) = \ln(x) \quad \leftrightarrow \quad dx = x \left[\left(a_u + \frac{1}{2} b_u^2 \right) dt + b_u dW \right]. \quad (151)$$

To demonstrate the generality of our procedure, we carry it out for another special case that is historically important.

Example: Square-root (Cramer) utility

The first utility function ever to be suggested was the square-root function $u(x) = x^{1/2}$, by Cramer in a 1728 letter to Daniel Bernoulli, partially reproduced in [?]. This function is invertible, namely $x(u) = u^2$, so that (Eq. 149) applies. We note that the square root, in a specific sense, sits between the linear function and the logarithm: $\lim_{x \rightarrow \infty} \frac{x^{1/2}}{x} = 0$ and $\lim_{x \rightarrow \infty} \frac{\ln(x)}{x^{1/2}} = 0$. Since linear utility produces additive dynamics and logarithmic utility produces multiplicative dynamics, we expect square-root utility to produce something in between or some mix. Substituting for $x(u)$ in (Eq. 149) and

carrying out the differentiations in (Eq. 149) we find

$$\underline{u}(\underline{x}) = \underline{x}^{1/2} \leftrightarrow dx = \left(2a_u \underline{x}^{1/2} + b_u^2 \right) dt + 2b_u \underline{x}^{1/2} dW. \quad (152)$$

The drift term contains a multiplicative element (by which we mean an element with \underline{x} -dependence) and an additive element. We see that the square-root utility function that lies between the logarithm and the linear function indeed represents a dynamic that is partly additive and partly multiplicative.

(Eq. 152) is reminiscent of the Cox-Ingersoll-Ross model [?] in financial mathematics, especially if $a_u < 0$. Similar dynamics, *i.e.* with a noise amplitude that is proportional to $\sqrt{\underline{x}}$, are also studied in the context of absorbing-state phase transitions in statistical physics [?, ?]. That a 300-year-old letter is related to recent work in statistical mechanics is not surprising: the problems that motivated the development of decision theory, and indeed of probability theory itself are far-from equilibrium processes. Methods to study such processes were only developed in the 20th century and constitute much of the work currently carried out in statistical mechanics.

2.7.4 Utility function from a dynamic

We now ask under what circumstances the procedure in (Eq. 149) can be inverted. When can a utility function be found for a given dynamic? In other words, what conditions does the dynamic dx have to satisfy so that optimization over time can be represented by optimization of expected net changes in utility $\underline{u}(\underline{x})$, or: when does an ergodicity mapping, $v(\underline{x})$, exist?

We ask whether a given dynamic can be mapped into a utility whose increments are described by Brownian motion, (Eq. 148).

The dynamic is an arbitrary Itô process

$$dx = a_x(\underline{x})dt + b_x(\underline{x})dW, \quad (153)$$

where $a_x(\underline{x})$ and $b_x(\underline{x})$ are arbitrary functions of \underline{x} . For this dynamic to translate into a Brownian motion for the utility, $\underline{u}(\underline{x})$ must satisfy the equivalent of (Eq. 149) with the special requirement that the coefficients a_u and b_u in (Eq. 148) be constants, namely

$$du = \underbrace{\left(a_x(\underline{x}) \frac{\partial \underline{u}}{\partial \underline{x}} + \frac{1}{2} b_x^2(\underline{x}) \frac{\partial^2 \underline{u}}{\partial \underline{x}^2} \right)}_{a_u} dt + \underbrace{b_x(\underline{x}) \frac{\partial \underline{u}}{\partial \underline{x}}}_{b_u} dW. \quad (154)$$

To avoid clutter, let's use Lagrange notation, namely a dash $-'$ – to denote a derivative. Explicitly, we arrive at two equations for the coefficients

$$a_u = a_x(\underline{x})\underline{u}' + \frac{1}{2} b_x^2(\underline{x})\underline{u}'' \quad (155)$$

and

$$b_u = b_x(\underline{x})\underline{u}'. \quad (156)$$

Differentiating (Eq. 156), it follows that

$$\underline{u}''(\underline{x}) = -\frac{b_u b_x'(\underline{x})}{b_x^2(\underline{x})}. \quad (157)$$

Substituting in (Eq. 155) for \underline{u}' and \underline{u}'' and solving for $a_x(\underline{x})$ we find the drift term as a function of the noise term,

$$a_x(\underline{x}) = \frac{a_u}{b_u} b_x(\underline{x}) + \frac{1}{2} b_x(\underline{x}) b_x'(\underline{x}). \quad (158)$$

In other words, knowledge of only the dynamic is sufficient to determine whether a corresponding utility function exists. We do not need to construct the utility function explicitly to know whether a pair of drift term and noise term is consistent or not.

Having determined for some dynamic that a consistent utility function exists, we can construct it by substituting for $b_x(\underline{x})$ in (Eq. 155). This yields a differential equation for \underline{u}

$$a_u = a_x(\underline{x}) \underline{u}' + \frac{b_u^2}{2 \underline{u}^2} \underline{u}'' \quad (159)$$

or

$$0 = -a_u \underline{u}'^2 + a_x(\underline{x}) \underline{u}'^3 + \frac{b_u^2}{2} \underline{u}'' \quad (160)$$

Overall, then the triplet noise term, drift term, utility function is interdependent. Given a noise term we can find consistent drift terms, and given a drift term we find a consistency condition (differential equation) for the utility function. These arguments may seem a little esoteric when first encountered, using bits and pieces from different fields of mathematics. But they constitute the actual physical story behind the fascinating history of decision theory. Again, we illustrate the procedure with an example.

Example: A curious-looking dynamic

Given a dynamic, it is possible to check whether it can be mapped into a utility function, and the utility function itself can be found. We consider the wealth dynamic

$$d\underline{x} = \left(\frac{a_u}{b_u} e^{-\underline{x}} - \frac{1}{2} e^{-2\underline{x}} \right) d\underline{t} + e^{-\underline{x}} dW. \quad (161)$$

We note that $a_x(\underline{x}) = \frac{a_u}{b_u} e^{-\underline{x}} - \frac{1}{2} e^{-2\underline{x}}$ and $b_x(\underline{x}) = e^{-\underline{x}}$. Equation (158) imposes conditions on the drift term $a_x(\underline{x})$ in terms of the noise term $b_x(\underline{x})$. Substituting in (Eq. 158) reveals that the consistency condition is satisfied by the dynamic in (Eq. 161). A typical trajectory of (Eq. 161) is shown in Fig. 11.

Because (Eq. 161) is internally consistent, it is possible to derive the corresponding utility function. Equation (156) is a first-order ordinary differential equation for $\underline{u}(\underline{x})$

$$\underline{u}'(\underline{x}) = \frac{b_u}{b_x(\underline{x})}, \quad (162)$$

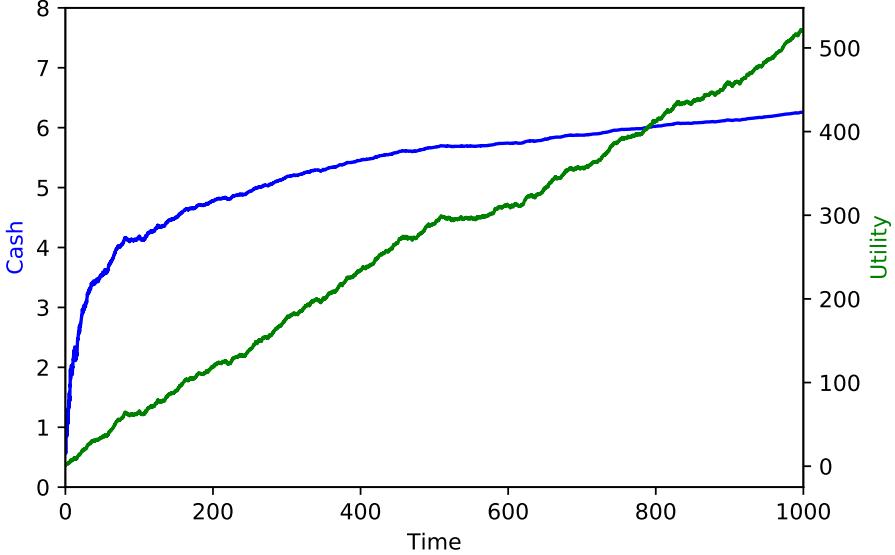


Figure 11: Typical trajectory $x(t)$ of the wealth dynamic (Eq. 161), with parameter values $a_u = 1/2$ and $b_u = 1$, and the corresponding Brownian motion $u(t)$. Note that the fluctuations in $x(t)$ become smaller for larger wealth.

which can be integrated to

$$u(x) = \int_0^x d\tilde{x} \frac{b_u}{b_x(\tilde{x})} + C, \quad (163)$$

with C an arbitrary constant of integration. This constant, incidentally, implies that only *changes* in utility are meaningful, as was pointed out by von Neumann and Morgenstern [?] – this robust feature is visible whether one thinks in dynamic terms and time averages or in terms of consistent measure-theoretic concepts and expectation values.

Substituting for $b_x(x)$ from (Eq. 161), (Eq. 162) becomes

$$u'(x) = b_u e^x, \quad (164)$$

which is easily integrated to

$$u(x) = b_u e^x + C, \quad (165)$$

plotted in Fig. 12. This exponential utility function is monotonic and therefore invertible – we knew that because the consistency condition is satisfied. The utility function is convex. From the perspective of expected-utility theory an individual behaving optimally according to this function would be labelled “risk-seeking.” The dynamical perspective corresponds to a qualitatively different interpretation: Under the dynamic (Eq. 161) the “risk-seeking” individual behaves optimally, in the sense that his wealth will grow faster than that of a risk-averse individual. What’s optimal is

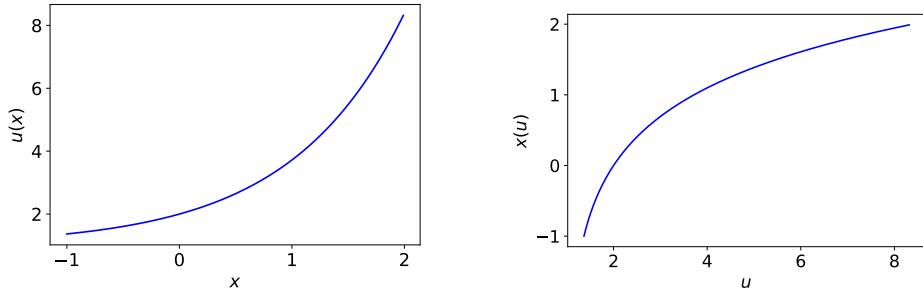


Figure 12: Exponential utility $u(x)$, (Eq. 165) with $b_u = 1$ and $C = 1$, is monotonic and unbounded and therefore invertible. Left panel: $u(x)$. Right panel: inverse $x(u)$.

determined by the dynamic, not by the individual. Of course the individual may choose whether to behave optimally. The dynamic (Eq. 161) has the feature that fluctuations in wealth become smaller as wealth grows. High wealth is therefore sticky – an individual will quickly fluctuate out of low wealth and into higher wealth. It will then tend to stay there.

2.8 The St Petersburg paradox

The problem known today as the St Petersburg paradox was suggested by Nicolaus Bernoulli¹⁶ in 1713 in his correspondence with Montmort [?]. It involves a hypothetical lottery for which the rate of change of expected wealth diverges for any finite ticket price. The expected-wealth paradigm would predict, therefore, that people are prepared to pay any price to enter the lottery. However, when the question is put to them, they rarely want to wager more than a few dollars. This is the paradox. It is the first well-documented example of the inadequacy of the expected-wealth paradigm as a model of human rationality. It was the primary motivating example for Daniel Bernoulli's and Cramer's development of the expected-utility paradigm [?].

In some sense it is a pity that this deliberately provocative and unrealistic lottery has played such an important role in the development of classical decision theory. It is quite unnecessary to invent a gamble with a diverging change in expected wealth to expose the flaws in the expected-wealth paradigm. The presence of infinities in the problem and its variously proposed solutions has caused much confusion, and permits objections on the grounds of physical impossibility. Such objections are unhelpful because they are not fundamental: they address only the gamble and not the decision paradigm. Nevertheless, the paradox is an indelible part not only of history but also of the current debate [?], and so we recount it here. We'll start by defining the lottery.

Example: St Petersburg lottery

The classical statement of the lottery is to imagine a starting prize of \$1 (originally the prize was in ducats). A fair coin is tossed: if it lands heads, the player wins the prize and the lottery ends; if it lands tails, the prize is doubled and the process is repeated. Therefore, the player wins \$2, \$4,

¹⁶Daniel's cousin. The Bernoulli family produced a remarkable number of famous mathematicians in the 17th and 18th centuries, who helped lay the foundations of applied mathematics and physics.

\$8 if the first head lands on the second, third, fourth toss, and so on. The player must buy a ticket, at price F , to enter the lottery. The question usually posed is: what is the largest F the player is willing to pay?

The lottery can be translated neatly into our gamble formalism:

$$q_j = \$2^{j-1} - F, \quad p_j = 2^{-j}, \quad (166)$$

for $j \in \{1, 2, 3, \dots\}$, i.e. the set of positive integers. The vast majority of observed payouts are small, but occasionally an extremely large payout (corresponding to a very long unbroken sequence of tails in the classical description) occurs. This is shown in the example trajectories in Fig. 13, where the lottery has been repeated additively.

From now on we will forget about the coin tosses, which are simply a mechanism for selecting one of the possible payouts. In effect, they are just a random number generator. Instead we shall work with the compact definition of the lottery in (Eq. 166) and assume it takes a fixed amount of time, δt , to play.

The rate of change of expected wealth is

$$\frac{\langle \delta x \rangle}{\delta t} = \frac{1}{\delta t} \sum_{j=1}^{\infty} p_j q_j \quad (167)$$

$$= \frac{1}{\delta t} \left(\$ \sum_{j=1}^{\infty} 2^{-j} 2^{j-1} - \sum_{j=1}^{\infty} 2^{-j} F \right) \quad (168)$$

$$= \frac{1}{\delta t} \left(\$ \sum_{j=1}^{\infty} \frac{1}{2} - F \right). \quad (169)$$

This diverges for any finite ticket price. Under the expected-wealth paradigm, this means that the lottery is favourable at any price.

This implausible conclusion, which does not accord with human behaviour, exposes the weakness of judging a gamble by its effect on expected wealth. Daniel Bernoulli suggested to resolve the paradox by adopting the expected-utility paradigm. His choice of utility function was the logarithm, $u(x) = \ln x$, which, as we now know, produces a decision rule equivalent to growth-rate optimisation under multiplicative repetition. This correspondence was not appreciated by Bernoulli: indeed 18th-century mathematics did not possess the concepts and language required to distinguish between averages over time and across systems, even though it had the basic arithmetic tools.

Unfortunately, Bernoulli made a mathematical error in the implementation of his own paradigm – accidentally he proposed two mutually inconsistent versions of utility theory in the paper that established the paradigm. Initially, the error had little impact, and it was corrected by Laplace in 1814 [?]. But Laplace didn't openly say he'd corrected an error, he just work with what he thought Bernoulli had meant. This politeness had awful consequences. In 1934 Menger [?], keen to get the story right, went back to the original text by Bernoulli. He didn't notice the error but rather got confused by it which led him to introduce a further error. Based on this car crash of scientific communication, Menger derived the infamous (wrong) claim we encountered in Sec. 2.7.2:

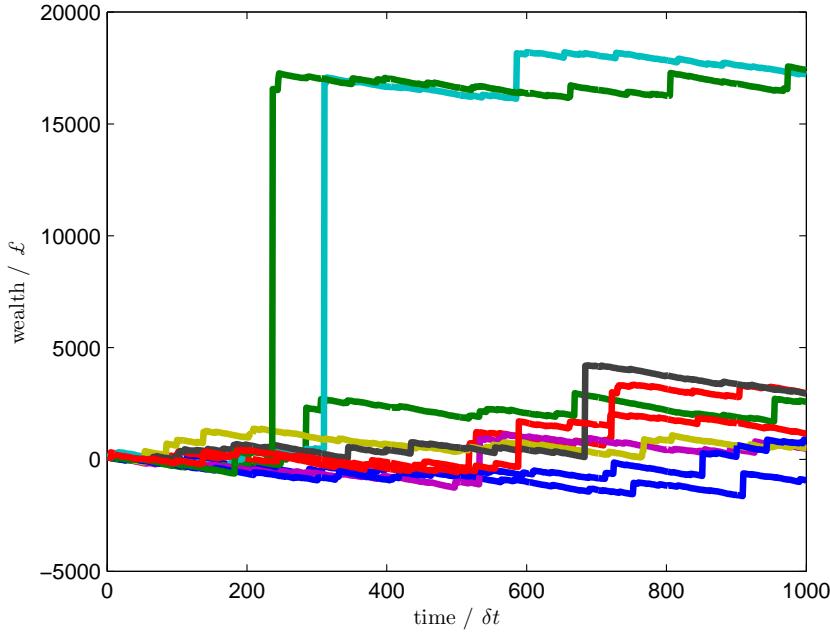


Figure 13: Wealth trajectories for the additively repeated St Petersburg lottery, with starting wealth, $\textcolor{teal}{x}(0) = \100 , and ticket price, $F = \$10$. Ten trajectories are plotted over 1,000 rounds.

utility functions must be bounded, with disastrous consequences for the budding neoclassical formalism. We will leave this most chequered part of the paradox's history alone – details can be found in [?]. Instead we will focus on what's usually presumed Bernoulli meant to write.

Example: Resolution by logarithmic utility

Instead of (Eq. 169), we calculate the rate of change of expected logarithmic utility,

$$\frac{\langle \delta \ln \textcolor{teal}{x} \rangle}{\delta t} = \frac{1}{\delta t} \sum_{j=1}^{\infty} \textcolor{teal}{p}_j [\ln(\textcolor{teal}{x} + \textcolor{teal}{q}_j) - \ln \textcolor{teal}{x}] \quad (170)$$

$$= \frac{1}{\delta t} \sum_{j=1}^{\infty} 2^{-j} \ln \left(\frac{\textcolor{teal}{x} + \$2^{j-1} - F}{\textcolor{teal}{x}} \right), \quad (171)$$

where $\textcolor{teal}{x}$ is the ticket buyer's wealth.

This is finite for all finite ticket prices less than the buyer's wealth plus the smallest prize: $F < \textcolor{teal}{x} + \1 . This can be shown by applying the ratio test.¹⁷ It may be positive or negative, depending on the values of F and $\textcolor{teal}{x}$. Fig. 14 shows the locus of points in the $(\textcolor{teal}{x}, F)$ -plane for which the sum is zero.

The utility paradigm is a model that resolves the paradox, in the sense that

¹⁷The ratio of the $(j+1)^{\text{th}}$ term to the j^{th} term in the sum tends to $1/2$ as $j \rightarrow \infty$.

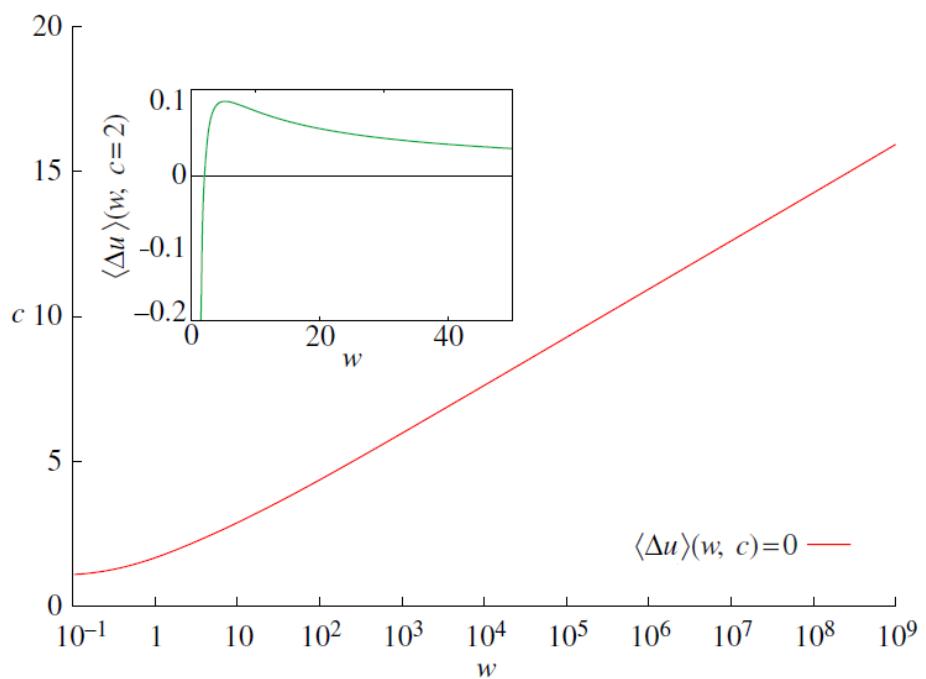


Figure 14: Locus of points in the (x, F) -plane for which the expected change in logarithmic utility is zero. The inset shows the expected change in utility as a function of x for $F = \$2$. Adapted from [?].

creates a world where players may decline to buy a ticket. Bernoulli argued for this resolution framework in plausible terms: the usefulness of a monetary gain depends on how much money you already have. He also argued specifically for the logarithm in plausible terms: the gain in usefulness should be proportional to the fractional gain it represents, $\delta u = \delta x/x$. Yet, the framework has left many unsatisfied: why does usefulness have this functional form? We provide this deeper reason by connecting the problem to dynamics and time, unlike Bernoulli. Had Bernoulli made the connection, he might have been less willing to accept Cramer's square-root utility function as an alternative, which, as we've seen, corresponds to a rather less intuitive dynamic.

Turning to our decision algorithm, we will assume that the lottery is repeated multiplicatively. This means, in effect, that the prizes and ticket price are treated as fractions of the player's wealth, such that the effect of each lottery is to multiply current wealth by a random factor,

$$r_j = \frac{x + \$2^{j-1} - F}{x}, \quad p_j = 2^{-j}. \quad (172)$$

This follows precisely our earlier treatment of a gamble with multiplicative dynamics, and we can apply our results directly. The time-average (exponential) growth rate is

$$\bar{g}_m = \frac{1}{\delta t} \lim_{T \rightarrow \infty} \left\{ \frac{1}{T} \sum_{\tau=1}^T \ln r(\tau) \right\} = \frac{1}{\delta t} \sum_{j=1}^{\infty} 2^{-j} \ln r_j, \quad (173)$$

which is identical to the expression for the rate of change of expected log-utility, (Eq. 171). This is, as we've discussed, because $v(x) = \ln(x)$ is the appropriate ergodicity mapping for multiplicative dynamics. The result is the same, but the interpretation is different: we have assumed less, only that our player is interested in the growth rate of his wealth and that he gauges this by imagining the outcome of an indefinite sequence of repeated lotteries.

Thus the locus in Fig. 14 also marks the decision threshold *versus* the null gamble under our decision axiom. The player can sensibly decline the gamble, even though it results in a divergent change in expected wealth. This is illustrated by comparing Fig. 15, which shows trajectories of multiplicatively repeated lotteries, with the additively repeated lotteries already seen in Fig. 13. The trajectories are based on the same sequences of lottery outcomes, only the mode of repetition is different. The simulation shows us visually what we have already gleaned by analysis: what appears favourable in the expected-wealth paradigm (corresponding to additive repetition) results in a disastrous decay of the player's wealth over time under a realistic dynamic.

As $F \rightarrow x + \$1$ from above in (Eq. 173), \bar{g}_m diverges negatively, since the first term in the sum is the logarithm of a quantity approaching zero. This corresponds to a lottery which can make the player bankrupt. The effect is also shown in the inset of Fig. 14.

Treatments based on multiplicative repetition have appeared sporadically in the literature, starting with Whitworth in 1870 [?, App. IV].¹⁸ It is related to

¹⁸Whitworth was dismissive of early utility theory: "The result at which we have arrived is not to be classed with the arbitrary methods which have been again and again propounded to evade the difficulty of the Petersburg problem.... Formulae have often been proposed,

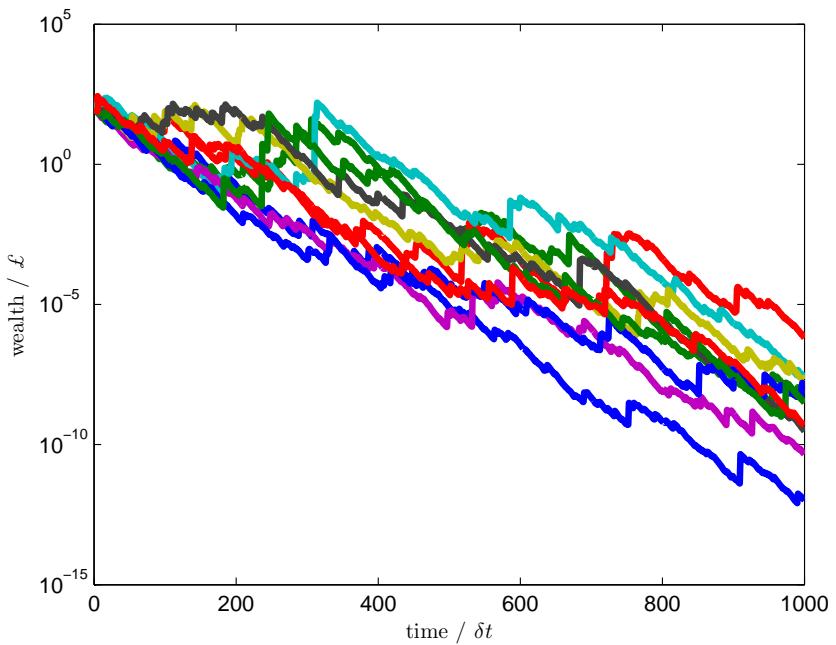


Figure 15: Wealth trajectories for the multiplicatively repeated St Petersburg lottery, with starting wealth, $x(0) = \$100$, and ticket price, $F = \$10$. Ten trajectories are plotted over 1,000 rounds. The realisations of the individual lotteries are the same as in Fig. 13 but the mode of repetition is different.

the famous Kelly Criterion [?]¹⁹, although Kelly did not explicitly treat the St Petersburg game, and tangentially to Itô’s lemma [?]. It appears as an exercise in a well-known text on information theory [?, Ex. 6.17]. Mainstream economics has ignored all this. A full and rigorous resolution of the paradox, including the epistemological significance of the shift from ensemble to time averages, was published recently by one of the present authors [?].

2.9 The insurance puzzle

The insurance contract is an important and ubiquitous type of economic transaction, which can be modelled as a gamble. However, it poses a puzzle [?]. In the expected-wealth paradigm, insurance contracts shouldn’t exist, because buying insurance would only be rational at a price at which it would be irrational to sell. More specifically:

1. To be viable, an insurer must charge an insurance premium of at least the expectation value of any claims that may be made against it, called the “net premium” [?, p. 1].
2. The insurance buyer therefore has to be willing to pay more than the net premium so that an insurance contract may be successfully signed.
3. Under the expected-wealth paradigm it is irrational to pay more than the net premium, and therefore insurance contracts should not exist.

In this picture, an insurance contract can only ever be beneficial to one party. It has the anti-symmetric property that the expectation value of one party’s gain is the expectation value of the other party’s loss.

The puzzle is that insurance contracts are observed to exist.²⁰ Why? Classical resolutions appeal to utility theory (*i.e.* psychology) and asymmetric information (*i.e.* deception). However, our decision theory naturally predicts contracts with a range of prices that increase the time-average growth rate for both buyer and seller. We illustrate this with an example drawn from maritime trade, in which the use of insurance has a very long history.²¹ A similar example was used by Bernoulli [?].

which have possessed the one virtue of presenting a finite result... but they have often had no intelligible basis to rest upon, or... sufficient care has not been taken to draw a distinguishing line between the significance of the result obtained, and the different result arrived at when the mathematical expectation is calculated.” Sadly he chose to place these revolutionary remarks in an appendix of a college probability textbook.

¹⁹Kelly was similarly unimpressed with the mainstream and noted in his treatment of decision theory, which he developed from the perspective of information theory and which is identical to ergodicity economics with multiplicative dynamics, that the utility function is “too general to shed any light on the specific problems of communication theory.”

²⁰Something of an understatement. The Bank for International Settlements estimated the market value of all the world’s derivatives contracts, which are essentially insurance contracts, as \$15 trillion in the first half of 2015 (see http://www.bis.org/statistics/d5_1.pdf). That’s six times the gross domestic product of the United Kingdom.

²¹Contracts between Babylonian traders and lenders were recorded around 1750 BC in the Code of Hammurabi. Chinese traders practised diversification by spreading cargoes across multiple vessels even earlier than this, in the third millennium BC.

Example: A shipping contract

We imagine a shipowner sending a cargo from St Petersburg to Amsterdam, with the following parameters:

- owner's wealth, $x_{\text{own}} = \$100,000$;
- gain on safe arrival of cargo, $G = \$4,000$;
- probability ship will be lost, $p = 0.05$;
- replacement cost of the ship, $C = \$30,000$; and
- voyage time, $\delta t = 1$ month.

An insurer with wealth $x_{\text{ins}} = \$1,000,000$ proposes to insure the voyage for a fee, $F = \$1,800$. If the ship is lost, the insurer pays the owner $L = G + C$ to make him good on the loss of his ship and the profit he would have made.

We phrase the decision the owner is facing as a choice between two gambles.

Definition The owner's gambles

Sending the ship uninsured corresponds to gamble o1

$$q_1^{(o1)} = G, \quad p_1^{(o1)} = 1 - p; \quad (174)$$

$$q_2^{(o1)} = -C, \quad p_2^{(o1)} = p. \quad (175)$$

Sending the ship fully insured corresponds to gamble o2

$$q_1^{(o2)} = G - F \quad p_1^{(o2)} = 1. \quad (176)$$

This is a trivial “gamble” because all risk has been transferred to the insurer.

We also model the insurer's decision whether to offer the contract as a choice between two gambles

Definition The insurer's gambles

Not insuring the ship corresponds to gamble i1, which is the null gamble

$$q_1^{(i1)} = 0 \quad p_1^{(i1)} = 1. \quad (177)$$

Insuring the ship corresponds to gamble i2

$$q_1^{(i2)} = +F, \quad p_1^{(i2)} = 1 - p; \quad (178)$$

$$q_2^{(i2)} = -L + F, \quad p_2^{(i2)} = p. \quad (179)$$

We ask whether the owner should sign the contract, and whether the insurer should have proposed it.

Example: Expected-wealth paradigm

In the expected-wealth paradigm (corresponding to additive repetition under the time paradigm) decision makers maximise the rate of change of

the expectation values of their wealths, according to (Eq. 127): Under this paradigm the owner collapses gamble o1 into the scalar

$$\bar{g}_a^{(o1)} = \frac{\langle \delta x \rangle}{\delta t} \quad (180)$$

$$= \frac{\langle q^{(o1)} \rangle}{\delta t} \quad (181)$$

$$= \frac{(1-p)G + p(-C)}{\delta t} \quad (182)$$

$$= \$2,300 \text{ per month}, \quad (183)$$

and gamble o2 into the scalar

$$\bar{g}_a^{(o2)} = \frac{\langle q^{(o2)} \rangle}{\delta t} \quad (184)$$

$$= \frac{(G - F)}{\delta t} \quad (185)$$

$$= \$2,200 \text{ per month}. \quad (186)$$

The difference, $\delta \bar{g}_a^o$, between the expected rates of change in wealth with and without a signed contract is the expected loss minus the fee per round trip,

$$\delta \bar{g}_a^o = \bar{g}_a^{(o2)} - \bar{g}_a^{(o1)} = \frac{pL - F}{\delta t}. \quad (187)$$

The sign of this difference indicates whether the insurance contract is beneficial to the owner. In the example this is not the case, $\delta \bar{g}_a^o = -\$100$ per month.

The insurer evaluates the gambles i1 and i2 similarly, with the result

$$\bar{g}_a^{(i1)} = \$0 \text{ per month}, \quad (188)$$

and

$$\bar{g}_a^{(i2)} = \frac{F - pL}{\delta t} \quad (189)$$

$$= \$100 \text{ per month}. \quad (190)$$

Again we compute the difference – the net benefit to the insurer that arises from signing the contract

$$\delta \bar{g}_a^i = \bar{g}_a^{(i2)} - \bar{g}_a^{(i1)} = \frac{F - pL}{\delta t}. \quad (191)$$

In the example this is $\delta \bar{g}_a^i = \$100$ per month, meaning that in the world of the expected-wealth paradigm the insurer will offer the contract.

Because only one party (the insurer) is willing to sign, no contract will come into existence. We could think that we got the price wrong, and the contract would be signed if offered at a different fee. But this is not the case, and that's the fundamental insurance puzzle: in the world created by expected-wealth

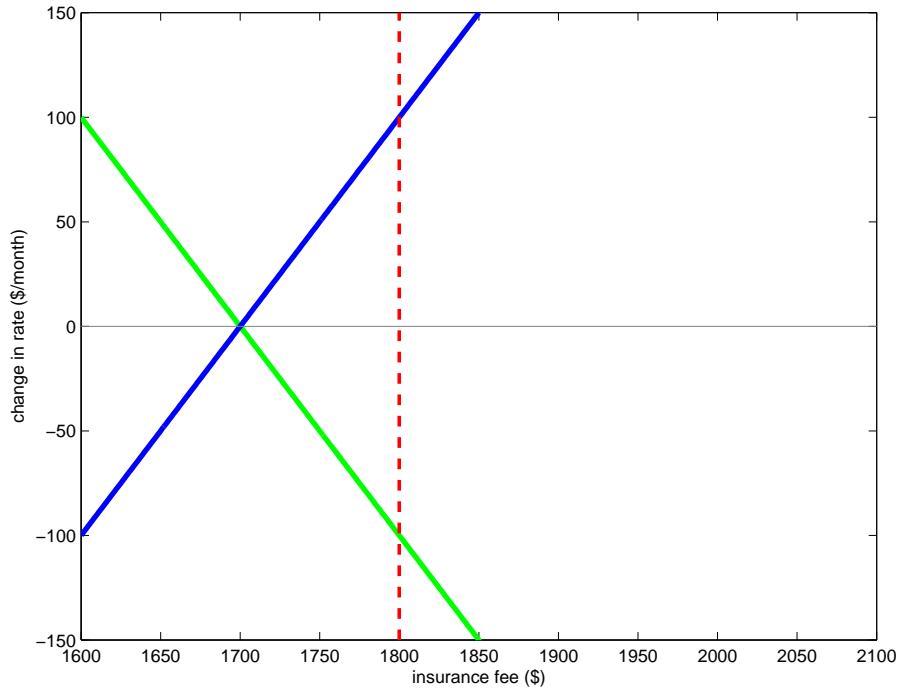


Figure 16: Change in the rate of change of expected wealth for the shipowner (green) and the insurer (blue) as a function of the insurance fee, F .

maximisation no price exists at which both parties will sign the contract.

Looking at (Eq. 187) and (Eq. 191) we notice the anti-symmetric relationship between the two expressions, $\delta\bar{g}_a^o = -\delta\bar{g}_a^i$. By symmetry, there can be no fee at which both expressions are positive. Hence there are no circumstances in the world created by the expected-wealth paradigm under which both parties will sign. Insurance contracts cannot exist in this world.

One party winning at the expense of the other makes insurance an unsavoury business in the expected-wealth paradigm. This is further illustrated in Fig. 16, which shows the change in the rate of change of expected wealth (the decision variable) for both parties as a function of the fee, F . There is no price at which the decision variable is positive for the both parties. The best they can do is to pick the price at which neither of them cares whether they sign or not.

In this picture, the existence of insurance contracts requires some asymmetry between the contracting parties, such as:

- different attitudes to bearing risk;
- different access to information about the voyage;
- different assessments of the riskiness of the voyage;
- one party to deceive, coerce, or gull the other into a bad decision.

It is difficult to believe that this is truly the basis for a market of the size and global reach of the insurance market.

2.9.1 Solution in the time paradigm

Example: Time paradigm

The insurance puzzle is resolved in the ‘time paradigm’, *i.e.* using the growth-optimal decision theory we have developed in this lecture and multiplicative repetition. Again, we pause to reflect what multiplicative repetition means compared to additive repetition. This is important because additive repetition is equivalent to the expected-wealth paradigm that created the insurance puzzle. Multiplicative repetition means that the ship owner sends out a ship and a cargo whose values are proportional to his wealth at the start of each voyage. A rich owner who has had many successful voyages will send out more cargo, a larger ship, or perhaps a *flotilla*, while an owner to whom the sea has been a cruel mistress will send out a small vessel until his luck changes. Under additive repetition, the ship owner would send out the same amount of cargo on each journey, irrespective of his wealth. Shipping companies of the size of Evergreen or Maersk would be inconceivable under additive repetition, where returns on successful investments are not reinvested.

The two parties seek to maximise

$$\bar{g}_m = \lim_{\Delta t \rightarrow \infty} \frac{\Delta v(x)}{\Delta t} = \frac{\langle \delta \ln x \rangle}{\delta t}, \quad (192)$$

where we have used the ergodic property of $\Delta v(x) = \Delta \ln x$ under multiplicative repetition.

The owner’s time-average growth rate without insurance is

$$\bar{g}_m^{o1} = \frac{(1-p) \ln(x_{\text{own}} + G) + p \ln(x_{\text{own}} - C) - \ln(x_{\text{own}})}{\delta t} \quad (193)$$

or 1.9% per month. His time-average growth rate with insurance is

$$\bar{g}_m^{o2} = \frac{\ln(x_{\text{own}} + G - F) - \ln(x_{\text{own}})}{\delta t} \quad (194)$$

or 2.2% per month. This gives a net benefit for the owner of

$$\delta \bar{g}_m^o = \bar{g}_m^{o1} - \bar{g}_m^{o2} \approx +0.24\% \text{ per month.} \quad (195)$$

The time paradigm thus creates a world where the owner will sign the contract.

What about the insurer? Without insurance, the insurer plays the null gamble, and

$$\bar{g}_m^{i1} = \frac{0}{\delta t} \quad (196)$$

or 0% per month. His time-average growth rate with insurance is

$$\bar{g}_m^{i2} = \frac{(1-p) \ln(x_{\text{ins}} + F) + p \ln(x_{\text{ins}} + F - L) - \ln(x_{\text{ins}})}{\delta t} \quad (197)$$

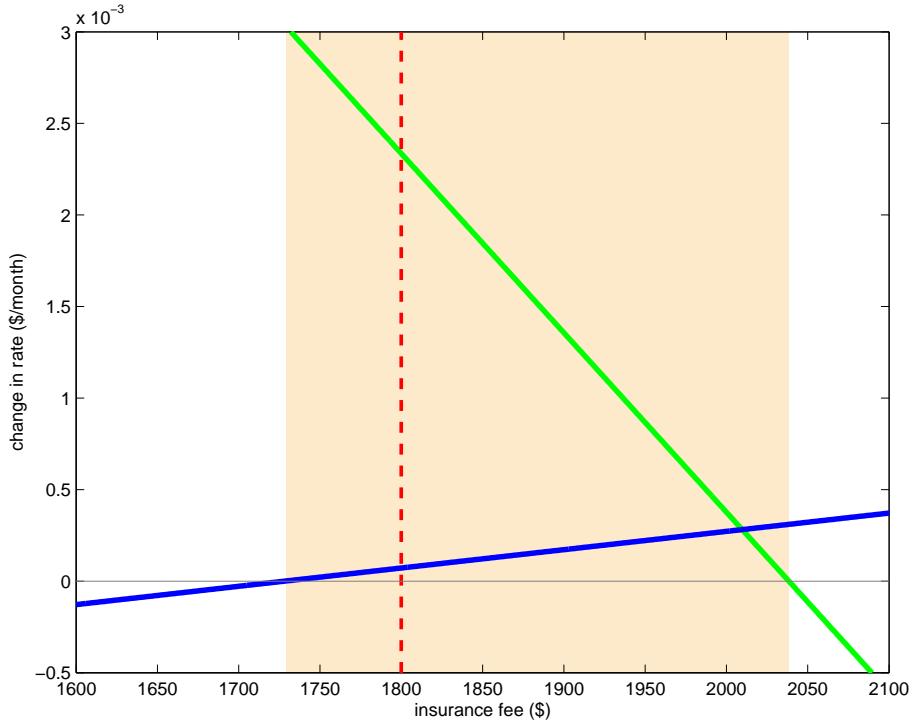


Figure 17: Change in the time-average growth rate of wealth for the shipowner (green) and the insurer (blue) as a function of the insurance fee, F . The mutually beneficial fee range is marked by the beige background.

or 0.0071% per month. The net benefit to the insurer is therefore also

$$\delta\bar{g}_m^i = \bar{g}_m^{i2} - \bar{g}_m^{i1} \quad (198)$$

i.e. 0.0071% per month. Unlike the expected wealth paradigm, the time paradigm with multiplicative repetition creates a world where an insurance contract can exist – there exists a range of fees F at which both parties gain from signing the contract!

We view this as the

Fundamental resolution of the insurance puzzle:

The buyer and seller of an insurance contract both sign when it increases the time-average growth rates of their wealths.

It requires no appeal to arbitrary utility functions or asymmetric circumstances, rather it arises naturally from the model of human decision-making that we have set out. Fig. 17 shows the mutually beneficial range of insurance fees predicted by our model. Generalizing, the message of the time paradigm is that business happens when both parties gain. In the world created by this model any agreement, any contract, any commercial interaction comes into existence because it is mutually beneficial.

2.9.2 The classical solution of the insurance puzzle

The classical solution of the insurance puzzle is identical to the classical solution of the St Petersburg paradox. Wealth is replaced by a non-linear utility function of wealth, which breaks the symmetry of the expected-wealth paradigm. While it is always true that $\delta \langle r \rangle_{\text{own}} = -\delta \langle r \rangle_{\text{ins}}$, the expected growth rates of non-linear utility functions don't share this anti-symmetry. A difference in the decision makers' wealths is sufficient, though often different utility functions are assumed for owner and insurer, which is a model that can create pretty much any behavior. The downside of a model with this ability is, of course, that it makes no predictions – nothing is ruled out, so the model cannot be falsified.

3 Populations

The previous chapter developed a model of individual behaviour based on an assumed dynamic imposed on wealth. If we know the stochastic process that describes individual wealth, then we also know what happens at population level – each individual is represented by a realisation of the process, and we can compute the dynamics of wealth distributions. We answer questions about inequality and poverty in a model economy which, for the moment, contains no interactions between individuals. We also gain an understanding of when and how results for finite populations differ from those for the infinite ensemble.

3.1 Every man for himself

We have seen that risk aversion constitutes optimal behaviour under the assumption of multiplicative wealth growth and over time scales that are long enough for systematic trends to be significant. In this chapter we will continue to explore our null model, **GBM**. By “explore” we mean that we will let the model generate its world – if individual wealth was to follow **GBM**, what kind of features of an economy would emerge? We will see that cooperation and the formation of social structure also constitute optimal behaviour.

GBM is more than a random variable. It’s a stochastic process, either a set of trajectories or a family of time-dependent random variables, depending on how we prefer to look at it. Both perspectives are informative in the context of economic modelling: from the set of trajectories we can judge what is likely to happen to an individual, *e.g.* by following a single trajectory for a long time; while the **PDF** of the random variable $x(t^*)$ at some fixed value of t^* tells us how wealth is distributed in our model.

We use the term wealth distribution to refer to the density function, $\mathcal{P}_x(x)$, and not the process of distributing wealth among people. This can be interpreted as follows. Imagine a population of N individuals. If I select a random individual, each having uniform probability $\frac{1}{N}$, then the probability of the selected individual having wealth greater than x is given by the CDF, $F_x(x) = \int_x^\infty \mathcal{P}_x(s)ds$. If N is large, then $\Delta x \mathcal{P}_x(x) N$ is the approximate number of individuals who have wealth between x and $x + \Delta x$. Thus, a broad wealth distribution with heavy tails indicates greater wealth inequality.

Examples:

- Under perfect equality everyone would have the same, meaning that the wealth distribution would be a Dirac delta function centred at the sample mean of x , that is

$$\mathcal{P}_x(x) = \delta(x - \langle x \rangle_N); \quad (199)$$

- Maximum inequality would mean that one individual owns everything and everyone else owns nothing, that is

$$\mathcal{P}_x(x) = \frac{N-1}{N} \delta(x - 0) + \frac{1}{N} \delta(x - N \langle x \rangle_N). \quad (200)$$

3.1.1 Log-normal distribution

At a given time, t , **GBM** produces a random variable, $x(t)$, with a log-normal distribution whose parameters depend on t . (A log-normally distributed random variable is one whose logarithm is a normally distributed random variable.) If each individual’s wealth follows **GBM**,

$$dx = x(\mu dt + \sigma dW), \quad (201)$$

with solution

$$x(t) = x(0) \exp \left[\left(\mu - \frac{\sigma^2}{2} \right) t + \sigma W(t) \right], \quad (202)$$

then we will observe a log-normal distribution of wealth at each moment in time:

$$\ln x(t) \sim \mathcal{N} \left(\ln x(0) + \left(\mu - \frac{\sigma^2}{2} \right) t, \sigma^2 t \right). \quad (203)$$

It will be convenient hereafter to assume the initial condition $\mathbf{x}(0) = 1$ (and, therefore, $\ln \mathbf{x}(0) = 0$) unless otherwise stated.

Note that the variance of $\ln \mathbf{x}(t)$ increases linearly in time. We will develop an understanding of this shortly. As we will see, it indicates that any meaningful measure of inequality will grow over time in our simple model. To see what kind of a wealth distribution (Eq. 203) is, it is worth spelling out the log-normal PDF:

$$\mathcal{P}_x(\mathbf{x}) = \frac{1}{\mathbf{x}\sqrt{2\pi\sigma^2 t}} \exp\left(-\frac{[\ln \mathbf{x} - (\mu - \frac{\sigma^2}{2})t]^2}{2\sigma^2 t}\right). \quad (204)$$

This distribution is the subject of a wonderful book [?], sadly out-of-print now. It will be useful to know some of its basic properties. Of particular importance is the expected wealth under this distribution. This is

$$\langle \mathbf{x}(t) \rangle = \exp(\mu t) \quad (205)$$

or, equivalently, $\ln \langle \mathbf{x}(t) \rangle = \mu t$. We could confirm this result by calculating $\langle \mathbf{x}(t) \rangle = \int_0^\infty s \mathcal{P}_x(s) ds$, but this would be laborious. Instead we use a neat trick, courtesy of [?, Chapter 4.2], which will come in handy again in Sec. 4.2.6. The idea is to derive from the stochastic differential equation for \mathbf{x} , like (Eq. 201), a solvable ordinary differential equation in the k^{th} moment, $\langle \mathbf{x}^k \rangle$. For the first moment we do this simply by taking expectations of both sides of (Eq. 201). The noise term vanishes to turn the SDE for \mathbf{x} into an ODE for $\langle \mathbf{x} \rangle$:

$$\langle d\mathbf{x} \rangle = \langle \mathbf{x}(\mu dt + \sigma dW) \rangle \quad (206)$$

$$d \langle \mathbf{x} \rangle = \langle \mathbf{x} \rangle \mu dt + \sigma \overbrace{\langle dW \rangle}^{=0} \quad (207)$$

$$= \langle \mathbf{x} \rangle \mu dt. \quad (208)$$

This is a very simple first-order linear differential equation, whose solution with initial condition $\mathbf{x}(0) = 1$ is given by (Eq. 205).

For $\mu > 0$ the expected wealth grows exponentially over time, as do its median and variance:

$$\text{median}[\mathbf{x}(t)] = \exp[(\mu - \sigma^2/2)t]; \quad (209)$$

$$\text{var}[\mathbf{x}(t)] = \exp(2\mu t)[\exp(\sigma^2 t) - 1]. \quad (210)$$

3.1.2 Two growth rates

We will recap briefly here one of our key ideas, covered in detail in Sec. 1.4, that the ensemble average of all possible trajectories of GBM grows at a different (faster) rate from that achieved by a single trajectory almost surely in the long-time limit. Understanding this difference was the key to developing a coherent theory of individual decision-making. We will see here that it is also crucial in understanding how wealth becomes distributed in a population of individuals whose wealths follow (Eq. 201) and, furthermore, how we can measure the inequality in such a distribution.

We recall from (Eq. 57) that the growth rate of the expected wealth is

$$g_{\langle \rangle} = \frac{d \ln \langle \mathbf{x} \rangle}{dt} = \mu, \quad (211)$$

and from (Eq. 64) that the time-average growth rate of wealth is

$$\bar{g} = \frac{d \langle \ln x \rangle}{dt} = \mu - \frac{\sigma^2}{2}. \quad (212)$$

3.1.3 Measuring inequality

In the case of **GBM** we have just seen how to compute the exact full wealth distribution, $\mathcal{P}_x(x)$. This is interesting but often we want only summary measures of the distribution. One summary measure of particular interest to economists is inequality. How much inequality is there in a distribution like (Eq. 203)? And how does this quantity increase over time under **GBM**, as we have suggested?

Clearly, to answer these questions, we must quantify “inequality”. In this section, and also in [?], we develop a natural way of measuring it, which makes use of the two growth rates we identified for the non-ergodic process. We will see that a particular inequality measure, known to economists as Theil’s second index of inequality [?], is the difference between typical wealth (growing at the time-average growth rate) and average wealth (growing at the ensemble-average growth rate) in our model. Thus, the difference between the time average and ensemble average, the essence of ergodicity breaking, is the fundamental driver of the dynamics of inequality.

The two limits of inequality are easily identified: minimum inequality means that everyone has the same wealth, and maximum inequality means that one individual has all the wealth and everyone else has nothing. (This assumes that wealth cannot become negative.) Quantifying inequality in any other distribution is reminiscent of the gamble problem. Recall that for gambles we wanted make statements of the type “this gamble is more desirable than that gamble”. We did this by collapsing a distribution to a scalar. Depending on the question that was being asked, the appropriate way of collapsing the distribution and the resulting scalar can be different (the scalar relevant to an insurance company may not be relevant to an individual). In the case of inequality we also have a distribution – the wealth distribution – and we want to make statements of the type “this distribution is more unequal than that distribution”. Again, this is done by collapsing the distribution to a scalar, and again many different choices of collapse and resulting scalar are possible. The Gini coefficient is a particularly well-known scalar of this type, the 80/20 ratio another. Indeed, there is a whole menagerie of inequality measures.

In this context the expectation value is an important quantity. For instance, if everyone has the same wealth, then everyone will own the average, $x_i = \langle x \rangle_N$, which converges to the expectation value for large N . Also, whatever the distribution of wealth, the total wealth is $N \langle x \rangle_N$ which converges to $N \langle x \rangle$ as N grows large. The growth rate of the expectation value, $g_{\langle \rangle}$, thus tells us how fast the average wealth and the total population wealth grow with probability one in a large ensemble. The time-average growth rate, \bar{g} , on the other hand, tells us how fast an individual’s wealth grows almost surely in the long run. If the typical individual’s wealth grows more slowly than the expectation value of wealth, then there must be atypical individuals with very large wealths to account for the difference. This insight suggests the following measure of inequality.

Definition Inequality, J , is the quantity whose growth rate is the

difference between expectation-value and time-average growth rates,

$$\frac{dJ}{dt} = g_{\langle \rangle} - \bar{g}. \quad (213)$$

Equation (213) defines the dynamic of inequality, and inequality itself is found by integrating over time:

$$J(t) = \int_0^t ds [g_{\langle \rangle}(s) - \bar{g}(s)]. \quad (214)$$

This definition may be used for dynamics other than **GBM**, as we shall discuss in Sec. 3.1.6. Whatever the wealth dynamic, typical minus average growth rates are informative of the dynamic of inequality. Within the **GBM** framework we can write the difference in growth rates as

$$\frac{dJ}{dt} = \frac{d \ln \langle x \rangle}{dt} - \frac{d \langle \ln x \rangle}{dt} \quad (215)$$

and integrate over time to get

$$J(t) = \ln \langle x(t) \rangle - \langle \ln x(t) \rangle. \quad (216)$$

This quantity is known as the mean logarithmic deviation (MLD) or Theil's second index of inequality [?]. This is rather remarkable. Our general inequality measure, (Eq. 214), evaluated for the specific case of **GBM**, turns out to be a well-known measure of inequality that economists have identified independently, without considering non-ergodicity and ensemble average and time average growth rates. Merely by insisting on measuring inequality well, Theil used the **GBM** model implicitly.²²

Substituting the known values of the two growth rates into (Eq. 213) and integrating, we can evaluate the Theil inequality as a function of time:

$$J(t) = \frac{\sigma^2}{2} t. \quad (217)$$

Thus we see that, in **GBM**, our measure of inequality increases indefinitely.

3.1.4 Wealth condensation

The log-normal distribution generated by **GBM** broadens indefinitely, (Eq. 210). Likewise, the inequality present in the distribution – measured as the time-integrated difference between ensemble and time average growth rates – grows without bound. A related property of **GBM** is the evolution towards wealth condensation. Wealth condensation means that a single individual will own a non-zero fraction of the total wealth in the population in the limit of large N , see *e.g.* [?]. In the present case an arbitrarily large share of the total wealth will be owned by an arbitrarily small share of the population.

One simple way of seeing this is to calculate the fraction of the population whose wealths are less than the expected wealth, *i.e.* $x(t) < \exp(\mu t)$. To do

²²Like Kelly's ideas about gambling [?], Theil's inequality measures were developed using information theory.

this, we define a new random variable, $z(t)$, whose distribution is the standard normal:

$$z(t) \equiv \frac{\ln x(t) - (\mu - \sigma^2/2)t}{\sigma t^{1/2}} \sim \mathcal{N}(0, 1). \quad (218)$$

We want to know the mass of the distribution with $\ln x(t) < \mu t$. This is equivalent to $z < \sigma t^{1/2}/2$, so the fraction below the expected wealth is

$$\Phi\left(\frac{\sigma t^{1/2}}{2}\right), \quad (219)$$

where Φ is the CDF of the standard normal distribution. This increases over time, tending to one as $t \rightarrow \infty$.

3.1.5 Rescaled wealth

Economists have arrived at many inequality measures, and have drawn up a list of conditions that particularly useful measures of inequality satisfy. Such measures are called “relative measures” [?, Appendix 4] and J is one of them.

One of the conditions is that inequality measures should not change when x is divided by the same factor for everyone. Since we are primarily interested in inequality in this section, we can remove absolute wealth levels from the analysis and study an object called the rescaled wealth.

Definition The rescaled wealth,

$$y_i(t) = \frac{x_i(t)}{\langle x(t) \rangle_N}, \quad (220)$$

is the proportion of the sample mean wealth – i.e. the wealth averaged over the finite population – owned by an individual.

This quantity is useful because its numerical value does not depend on the currency used: it is a dimensionless number. Thus if my rescaled wealth is $y_i(t) = 1/2$, it means that my wealth is half the average wealth, irrespective of whether I measure it in Kazakhstani Tenge or in Swiss Francs. The sample mean rescaled wealth is easily calculated:

$$\langle y_i(t) \rangle_N = \left\langle \frac{x_i(t)}{\langle x(t) \rangle_N} \right\rangle_N = 1. \quad (221)$$

If the population size, N , is large enough, then we might expect the sample mean wealth, $\langle x(t) \rangle_N$, to be close to the ensemble average, $\langle x(t) \rangle$, which is simply its $N \rightarrow \infty$ limit. We will discuss more carefully when this approximation holds for wealths following GBM in Sec. 3.2. Let’s assume for now that it does. The rescaled wealth is then well approximated as

$$y_i(t) = \frac{x_i(t)}{\langle x(t) \rangle} = x_i(t) \exp(-\mu t). \quad (222)$$

Now that we have an expression for y in terms of x and t , we can derive the dynamic for rescaled wealth using Itô’s formula (just as we did to find the

wealth dynamic for a general utility function in Sec. 2.7.3). We start with

$$dy = \frac{\partial y}{\partial t} dt + \frac{\partial y}{\partial x} dx + \frac{1}{2} \frac{\partial^2 y}{\partial x^2} dx^2 \quad (223)$$

$$= -\mu y dt + \frac{y}{x} dx, \quad (224)$$

and then substitute (Eq. 201) for dx to get

$$dy = y \sigma dW. \quad (225)$$

So $y(t)$ follows a very simple GBM with zero drift and volatility σ . This means that rescaled wealth, like wealth, has an ever-broadening log-normal distribution:

$$\ln y(t) \sim \mathcal{N}\left(-\frac{\sigma^2}{2}t, \sigma^2 t\right). \quad (226)$$

Finally, noting that $\langle \ln y \rangle = \langle \ln x \rangle - \ln \langle x \rangle$ gives us a simple expression for our inequality measure in (Eq. 216) in terms of the rescaled wealth:

$$J(t) = -\langle \ln y \rangle. \quad (227)$$

3.1.6 u -normal distributions and Jensen's inequality

So far we have confined our analysis to GBM, where wealths follow the dynamic specific by (Eq. 201). However, as we discussed in the context of gambles, other wealth dynamics are possible. In particular, we explored the dynamics corresponding to invertible utility functions, where utility executes a BM with drift as in (Eq. 148):

$$du = a_u dt + b_u dW. \quad (228)$$

Under this dynamic, utility is normally distributed,

$$u(x(t)) \sim \mathcal{N}(a_u t, b_u^2 t), \quad (229)$$

and we can say that wealth has a “ u -normal” distribution. For GBM, the corresponding utility function is, as we know, $u(x) = \ln x$, and u -normal becomes log-normal.

Replacing the logarithm in (Eq. 216) by the general utility function gives a general expression for our wealth inequality measure,

$$J_u(t) = u(\langle x(t) \rangle) - \langle u(x(t)) \rangle. \quad (230)$$

It's not easy to write a general expression for $J_u(t)$ in only t and the model parameters a_u and b_u , because it would involve the solution of the general wealth dynamic in (Eq. 149). However, we can still say something about how inequality evolves. Let's see what happens if we start with perfect equality, $x_i(0) = x_0$ with x_0 fixed, and then let wealths evolve a little to $x(\Delta t) = x_0 + \Delta x$, where Δx is a random wealth increment generated by the wealth dynamic. The change in inequality would be

$$\Delta J_u = u(\langle x_0 + \Delta x \rangle) - \langle u(x_0 + \Delta x) \rangle, \quad (231)$$

since $u(\langle x_0 \rangle) = \langle u(x_0) \rangle = u(x_0)$.

We can now appeal to Jensen's inequality: if u is a concave function, like the logarithm, then $\Delta J_u \geq 0$; while if u is convex, like the curious exponential in (Eq. 165), then $\Delta J_u \leq 0$. The only cases for which $\Delta J_u = 0$ are if Δx is non-random or if u is linear. Thus, it is both randomness and the nonlinearity of the utility function – or ergodicity transformation, if we make that equivalence – that creates a difference in growth rates and generates inequality.

3.1.7 power-law resemblance

It is an established empirical observation [?] that the upper tails of real wealth distributions look more like a power-law than a log-normal. Our trivial model does not strictly reproduce this feature, but it is instructive to compare the log-normal distribution to a power-law distribution. A power-law PDF has the asymptotic form

$$\mathcal{P}_x(x) = x^{-\alpha}, \quad (232)$$

for large arguments x . This implies that the logarithm of the PDF is proportional to the logarithm of its argument, $\ln \mathcal{P}_x(x) = -\alpha \ln x$. Plotting one against the other will yield a straight line, the slope being the exponent $-\alpha$.

Determining whether an empirical observation is consistent with such behaviour is difficult because the behaviour to be observed is in the tail (large x) where data are, by definition, sparse. A quick-and-dirty way of checking for possible power-law behaviour is to plot an empirical PDF against its argument on log-log scales, look for a straight line, and measure the slope. However, plotting any distribution on any type of scales results in some line. It may not be a straight line but it will have some slope everywhere. For a known distribution (power-law or not) we can interpret this slope as a local apparent power-law exponent.

What is the local apparent power-law exponent of a log-normal wealth distribution near the expectation value $\langle x \rangle = \exp(\mu t)$, *i.e.* in the upper tail where approximate power-law behaviour has been observed empirically? The logarithm of (Eq. 204) is

$$\ln \mathcal{P}(x) = -\ln \left(x \sqrt{2\pi\sigma^2 t} \right) - \frac{[\ln x - (\mu - \frac{\sigma^2}{2})t]^2}{2\sigma^2 t} \quad (233)$$

$$= -\ln x - \frac{\ln(2\pi\sigma^2 t)}{2} - \frac{(\ln x)^2 - 2(\mu - \frac{\sigma^2}{2})t \ln x + (\mu - \frac{\sigma^2}{2})^2 t^2}{2\sigma^2 t}. \quad (234)$$

Collecting terms in powers of $\ln x$ we find

$$\ln \mathcal{P}(x) = -\frac{(\ln x)^2}{2\sigma^2 t} + \left(\frac{\mu}{\sigma^2} - \frac{3}{2} \right) \ln x - \frac{\ln(2\pi\sigma^2 t)}{2} - \frac{(\mu - \frac{\sigma^2}{2})^2 t}{2\sigma^2} \quad (235)$$

with local slope, *i.e.* apparent exponent,

$$\frac{d \ln \mathcal{P}(x)}{d \ln x} = -\frac{1}{\sigma^2 t} + \frac{\mu}{\sigma^2} - \frac{3}{2}. \quad (236)$$

Near $\langle x \rangle$, $\ln x \sim \mu t$ so that the first two terms cancel approximately. Here the distribution will resemble a power-law with exponent $-3/2$ when plotted on doubly logarithmic scales. (The distribution will also look like a power-law where the first term is much smaller than the others, *e.g.* where $\ln x \ll \sigma^2 t$.)

We don't believe that such empirically observed power-laws are merely a manifestation of this mathematical feature. Important real-world mechanisms that broaden real wealth distributions, *i.e.* concentrate wealth, are missing from the null model. However, it is interesting that the trivial model of **GBM** reproduces so many qualitative features of empirical observations.

3.2 Finite populations

So far we have considered the properties of the random variable, $\mathbf{x}(t)$, generated by **GBM** at a fixed time, t . Most of the mathematical objects we have discussed are, strictly speaking, relevant only in the limit $N \rightarrow \infty$, where N is the number of realisations of this random variable. For example, the expected wealth, $\langle \mathbf{x}(t) \rangle$, is the limit of the sample mean wealth

$$\langle \mathbf{x}(t) \rangle_N \equiv \frac{1}{N} \sum_{i=1}^N \mathbf{x}_i(t), \quad (237)$$

as the sample size, N , grows large. In reality, human populations can be very large, say $N \sim 10^7$ for a nation state, but they are most certainly finite. Therefore, we need to be diligent and ask what the effects of this finiteness are. In particular, we will focus on the sample mean wealth under **GBM**. For what values of μ , σ , t , and N is this well approximated by the expectation value? And when it is not, what does it resemble?

3.2.1 Sums of log-normals

In [?] we studied the sample mean of **GBM**, which we termed the “partial ensemble average” (PEA). This is the average of N independent realisations of the random variable $\mathbf{x}(t)$, (Eq. 237). Here we sketch out some simple arguments about how this object depends on N and t .

Considering the two growth rates in Sec. 3.1.2, we anticipate the following tension:

- A) for large N , the PEA should resemble the expectation value, $\exp(\mu t)$;
- B) for long t , all trajectories in the sample – and, therefore, the sample mean itself – should grow like $\exp[(\mu - \sigma^2/2)t]$.

Situation A – when a sample mean resembles the corresponding expectation value – is known in statistical physics as “self-averaging.” A simple strategy for estimating when this occurs is to look at the relative variance of the PEA,

$$R \equiv \frac{\text{var}[\langle \mathbf{x}(t) \rangle_N]}{\langle \langle \mathbf{x}(t) \rangle \rangle_N^2}. \quad (238)$$

To be explicit, here the $\langle \cdot \rangle$ and $\text{var}(\cdot)$ operators, without N as a subscript, refer to the mean and variance over all possible PEAs. The PEAs themselves, taken over finite samples of size N , are denoted $\langle \cdot \rangle_N$. Equation (238) simplifies to

$$R = \frac{\frac{1}{N} \text{var}[\mathbf{x}(t)]}{\langle \mathbf{x}(t) \rangle^2}, \quad (239)$$

into which we insert (Eq. 205) and (Eq. 210) to get an expression in terms of the **GBM** model parameters:

$$R = \frac{e^{\sigma^2 t} - 1}{N}. \quad (240)$$

If $R \ll 1$, then the PEA will likely be close to its own expectation value, which is equal to the expectation value of the **GBM**. Therefore, $\langle \mathbf{x}(t) \rangle_N \approx \langle \mathbf{x}(t) \rangle$ when

$$t < \frac{\ln N}{\sigma^2}. \quad (241)$$

This hand-waving tells us roughly when the large-sample – or, as we see from (Eq. 241), short-time or low-volatility – self-averaging regime holds. A more careful estimate of the cross-over time in (Eq. 257) is a factor of 2 larger, as we shall see in Sec. 3.2.2, but the scaling is identical.

For $t > \ln N/\sigma^2$, the growth rate of the PEA transitions from μ to its $t \rightarrow \infty$ limit of $\mu - \sigma^2/2$ (Situation B). Another way of viewing this is to think about what dominates the average. For early times in the process, all trajectories are close together and none dominate the PEA. However, as time goes by the distribution broadens exponentially. Since each trajectory contributes with the same weight to the PEA, after some time the PEA will be dominated by the maximum in the sample,

$$\langle \mathbf{x}(t) \rangle_N \approx \frac{1}{N} \max_{i=1}^N \{ \mathbf{x}_i(t) \}. \quad (242)$$

All of these features are illustrated in Fig. 18.

Self-averaging stops when even the “luckiest” trajectory is no longer close to the expectation value $\exp(\mu t)$. This is guaranteed to happen eventually because the probability for a trajectory to reach $\exp(\mu t)$ decreases towards zero as t grows, as we saw in Sec. 3.1.4. Naturally, this takes longer for larger samples, which have more chances to contain a lucky trajectory.

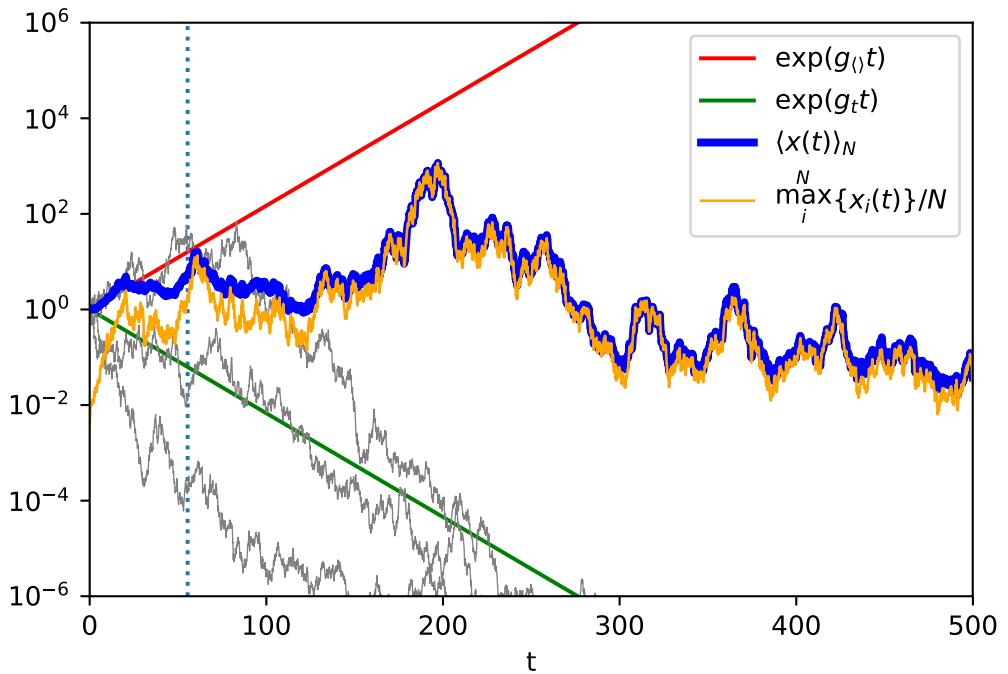


Figure 18: PEA and maximum in a finite ensemble of size $N = 256$. **Red line:** expectation value $\langle x(t) \rangle$. **Green line:** exponential growth at the time-average growth rate. In the $t \rightarrow \infty$ limit all trajectories grow at this rate. **Yellow line:** contribution of the maximum value of any trajectory at time t to the PEA. **Blue line:** PEA $\langle x(t) \rangle_N$. **Vertical line:** Crossover – for $t > t_c = \frac{2 \ln N}{\sigma^2}$ the maximum begins to dominate the PEA (the yellow line approaches the blue line). **Grey lines:** randomly chosen trajectories – any typical trajectory soon grows at the time-average growth rate. **Parameters:** $N = 256$, $\mu = 0.05$, $\sigma = \sqrt{0.2}$.

In [?] we analysed PEAs of GBM analytically and numerically. Using (Eq. 202) the PEA can be written as

$$\langle \mathbf{x} \rangle_{\mathcal{N}} = \frac{1}{\mathcal{N}} \sum_{i=1}^{\mathcal{N}} \exp \left[\left(\mu - \frac{\sigma^2}{2} \right) t + \sigma W_i(t) \right], \quad (243)$$

where $\{W_i(t)\}_{i=1\dots\mathcal{N}}$ are \mathcal{N} independent realisations of the Wiener process. Taking the deterministic part out of the sum, we can write

$$\langle \mathbf{x} \rangle_{\mathcal{N}} = \exp \left[\left(\mu - \frac{\sigma^2}{2} \right) t \right] \frac{1}{\mathcal{N}} \sum_{i=1}^{\mathcal{N}} \exp \left(t^{1/2} \sigma \xi_i \right), \quad (244)$$

where $\{\xi_i\}_{i=1\dots\mathcal{N}}$ are \mathcal{N} independent standard normal variates.

We found that typical trajectories of PEAs grow at $g_{\langle \cdot \rangle}$ up to a time t_c that is logarithmic in \mathcal{N} , meaning $t_c \propto \ln \mathcal{N}$. This is consistent with our analytical sketch. After this time, typical PEA trajectories begin to deviate from expectation-value behaviour, and eventually their growth rate converges to g_t . While the two limiting behaviours $\mathcal{N} \rightarrow \infty$ and $t \rightarrow \infty$ can be computed exactly, what happens in between is less straightforward. The PEA is a random object outside these limits.

A quantity of crucial interest to us is the exponential growth rate experienced by the PEA,

$$g_{\text{est}}(t, \mathcal{N}) \equiv \frac{\ln(\langle \mathbf{x}(t) \rangle_{\mathcal{N}}) - \ln(\mathbf{x}(0))}{t - 0} = \frac{1}{t} \ln(\langle \mathbf{x}(t) \rangle_{\mathcal{N}}). \quad (245)$$

In [?] we proved that the $t \rightarrow \infty$ limit for any (finite) \mathcal{N} is the same as for the case $\mathcal{N} = 1$,

$$\lim_{t \rightarrow \infty} g_{\text{est}}(t, \mathcal{N}) = \mu - \frac{\sigma^2}{2} \quad (246)$$

for all $\mathcal{N} \geq 1$. Substituting (Eq. 244) in (Eq. 245) produces

$$g_{\text{est}}(t, \mathcal{N}) = \mu - \frac{\sigma^2}{2} + \frac{1}{t} \ln \left(\frac{1}{\mathcal{N}} \sum_{i=1}^{\mathcal{N}} \exp(t^{1/2} \sigma \xi_i) \right) \quad (247)$$

$$= \mu - \frac{\sigma^2}{2} - \frac{\ln \mathcal{N}}{t} + \frac{1}{t} \ln \left(\sum_{i=1}^{\mathcal{N}} \exp(t^{1/2} \sigma \xi_i) \right). \quad (248)$$

We didn't look in [?] at the expectation value of $g_{\text{est}}(t, \mathcal{N})$ for finite time and finite samples, but it's an interesting object that depends on \mathcal{N} and t but is not stochastic. Note that this is not g_{est} of the expectation value, which would be the $\mathcal{N} \rightarrow \infty$ limit of (Eq. 245). Instead it is the $S \rightarrow \infty$ limit,

$$\langle g_{\text{est}}(t, \mathcal{N}) \rangle = \frac{1}{t} \langle \ln(\langle \mathbf{x}(t) \rangle_{\mathcal{N}}) \rangle = f(\mathcal{N}, t), \quad (249)$$

where, as previously, $\langle \cdot \rangle$ without subscript refers to the average over all possible samples, *i.e.* $\lim_{S \rightarrow \infty} \langle \cdot \rangle_S$. The last two terms in (Eq. 248) suggest an exponential relationship between ensemble size and time. The final term is a tricky stochastic object on which the properties of the expectation value in (Eq. 249) will hinge. This term will be the focus of our attention: the sum of exponentials of normal random variates or, equivalently, log-normal variates.

3.2.2 The random energy model

Since the publication of [?] we have learned, thanks to discussions with J.-P. Bouchaud, that the key object in (Eq. 248) – the sum log-normal random variates – has been of interest to the mathematical physics community since the 1980s. The reason for this is Derrida’s random energy model [?, ?], which we will describe here. This section is very “physicsy” and the key results are in (Eq. 262) and (Eq. 263) – it’s safe to skip to them, if you like.

The model is defined as follows. Imagine a system whose energy levels are $2^K = \text{N}$ normally-distributed random numbers, ξ_i (corresponding to K spins). This is a very simple model of a disordered system, such as a spin glass, the idea being that the system is so complicated that we “give up” and simply model its energy levels as realisations of a random variable. (We denote the number of spins by K and the number of resulting energy levels by N , while Derrida uses N for the number of spins). The partition function is then

$$Z = \sum_{i=1}^{\text{N}} \exp\left(\beta J \sqrt{\frac{K}{2}} \xi_i\right), \quad (250)$$

where the inverse temperature, β , is measured in appropriate units, and the scaling in K is chosen so as to ensure an extensive thermodynamic limit [?, p. 79]. J is a constant that will be determined below. The logarithm of the partition function gives the Helmholtz free energy,

$$F = -\frac{\ln Z}{\beta} \quad (251)$$

$$= -\frac{1}{\beta} \ln \left[\sum_{i=1}^{\text{N}} \exp\left(\beta J \sqrt{\frac{K}{2}} \xi_i\right) \right]. \quad (252)$$

Like the growth rate estimator in (Eq. 245), this involves a sum of log-normal variates and, indeed, we can rewrite (Eq. 248) as

$$\text{g}_{\text{est}} = \mu - \frac{\sigma^2}{2} - \frac{\ln \text{N}}{t} - \frac{\beta F}{t}, \quad (253)$$

which is valid provided that

$$\beta J \sqrt{\frac{K}{2}} = \sigma t^{1/2}. \quad (254)$$

Equation (254) does not give a unique mapping between the parameters of our GBM, (σ, t) , and the parameters of the REM, (β, K, J) . Equating (up to multiplication) the constant parameters, σ and J , in each model gives us a specific mapping:

$$\sigma = \frac{J}{\sqrt{2}} \quad \text{and} \quad t^{1/2} = \beta \sqrt{K}. \quad (255)$$

The expectation value of g_{est} is interesting. The only random object in (Eq. 253) is F . Knowing $\langle F \rangle$ thus amounts to knowing $\langle \text{g}_{\text{est}} \rangle$. In the statistical mechanics of the random energy model, $\langle F \rangle$ is of key interest and so much about it is known. We can use this knowledge thanks to the mapping between the two problems.

Derrida identifies a critical temperature,

$$\frac{1}{\beta_c} \equiv \frac{J}{2\sqrt{\ln 2}}, \quad (256)$$

above and below which the expected free energy scales differently with K and β . This maps to a critical time scale in [GBM](#),

$$t_c = \frac{2 \ln \mathcal{N}}{\sigma^2}, \quad (257)$$

with high temperature ($1/\beta > 1/\beta_c$) corresponding to short time ($t < t_c$) and low temperature ($1/\beta < 1/\beta_c$) corresponding to long time ($t > t_c$). Note that t_c in (Eq. 257) scales identically with \mathcal{N} and σ as the transition time, (Eq. 241), in our sketch.

In [?], $\langle F \rangle$ is computed in the high-temperature (short-time) regime as

$$\langle F \rangle = E - S/\beta \quad (258)$$

$$= -\frac{K}{\beta} \ln 2 - \frac{\beta K J^2}{4}, \quad (259)$$

and in the low-temperatures (long-time) regime as

$$\langle F \rangle = -K J \sqrt{\ln 2}. \quad (260)$$

Short time

We look at the short-time behavior first (high $1/\beta$, (Eq. 259)). The relevant computation of the entropy S in [?] involves replacing the number of energy levels $\mathcal{N}(E)$ by its expectation value $\langle \mathcal{N}(E) \rangle$. This is justified because the standard deviation of this number is $\sqrt{\mathcal{N}}$ and relatively small when $\langle \mathcal{N}(E) \rangle > 1$, which is the interesting regime in Derrida's case.

For spin glasses, the expectation value of F is interesting, supposedly, because the system may be self-averaging and can be thought of as an ensemble of many smaller sub-systems that are essentially independent. The macroscopic behavior is then given by the expectation value.

Taking expectation values and substituting from (Eq. 259) in (Eq. 253) we find

$$\langle g_{\text{est}} \rangle^{\text{short}} = \mu - \frac{\sigma^2}{2} + \frac{1}{t} \frac{K J^2}{4 T^2}. \quad (261)$$

From (Eq. 254) we know that $t = \frac{K J^2}{2 \sigma^2 T^2}$, which we substitute to find

$$\langle g_{\text{est}} \rangle^{\text{short}} = \mu. \quad (262)$$

This is the correct behavior in the short-time regime.

Long time

Next, we turn to the expression for the long-time regime (low temperature, (Eq. 260)). Again taking expectation values and substituting, this time from (Eq. 260) in (Eq. 253), we find for long times

$$\langle g_{\text{est}} \rangle^{\text{long}} = \mu - \frac{\sigma^2}{2} - \frac{\ln \mathcal{N}}{t} + \sqrt{\frac{2 \ln \mathcal{N}}{t}} \sigma, \quad (263)$$

which has the correct long-time asymptotic behavior. The form of the correction to the time-average growth rate in (Eq. 263) is consistent with [?] and [?], where it was found that approximately $\mathcal{N} = \exp(\mathfrak{t})$ systems are required for ensemble-average behavior to be observed for a time t , so that the parameter $\ln \mathcal{N}/t$ controls which regime dominates. If the parameter is small, then (Eq. 263) indicates that the long-time regime is relevant.

Figure 19 is a direct comparison between the results derived here, based on [?], and numerical results using the same parameter values as in [?], namely $\mu = 0.05$, $\sigma = \sqrt{0.2}$, $\mathcal{N} = 256$ and $S = 10^5$.

Notice that $\langle g_{\text{est}} \rangle$ is not the (local) time derivative $\frac{\partial}{\partial t} \langle \ln(\langle x \rangle_{\mathcal{N}}) \rangle$, but a time-average growth rate, $\left\langle \frac{1}{t} \ln \left(\frac{\langle x(t) \rangle_{\mathcal{N}}}{\langle x(0) \rangle_{\mathcal{N}}} \right) \right\rangle$. It is remarkable that the expectation value $\langle g_{\text{est}}(\mathcal{N}, t) \rangle$ so closely reflects the median, $q_{0.5}$, of $\langle x \rangle_{\mathcal{N}}$, *i.e.*

$$q_{0.5}(\langle x(t) \rangle_{\mathcal{N}}) \approx \exp(\langle g_{\text{est}}(\mathcal{N}, t) \rangle t). \quad (264)$$

In [?] it was discussed in detail that $g_{\text{est}}(1, t)$ is an ergodic observable for (Eq. 201), in the sense that $\langle g_{\text{est}}(1, t) \rangle = \lim_{t \rightarrow \infty} g_{\text{est}}$. The relationship in (Eq. 264) is far more subtle. The typical behavior of GBM PEAs is complicated outside the limits $\mathcal{N} \rightarrow \infty$ or $t \rightarrow \infty$, where growth rates are time-dependent. This complicated behaviour is well represented by an approximation that uses physical insights into spin glasses.

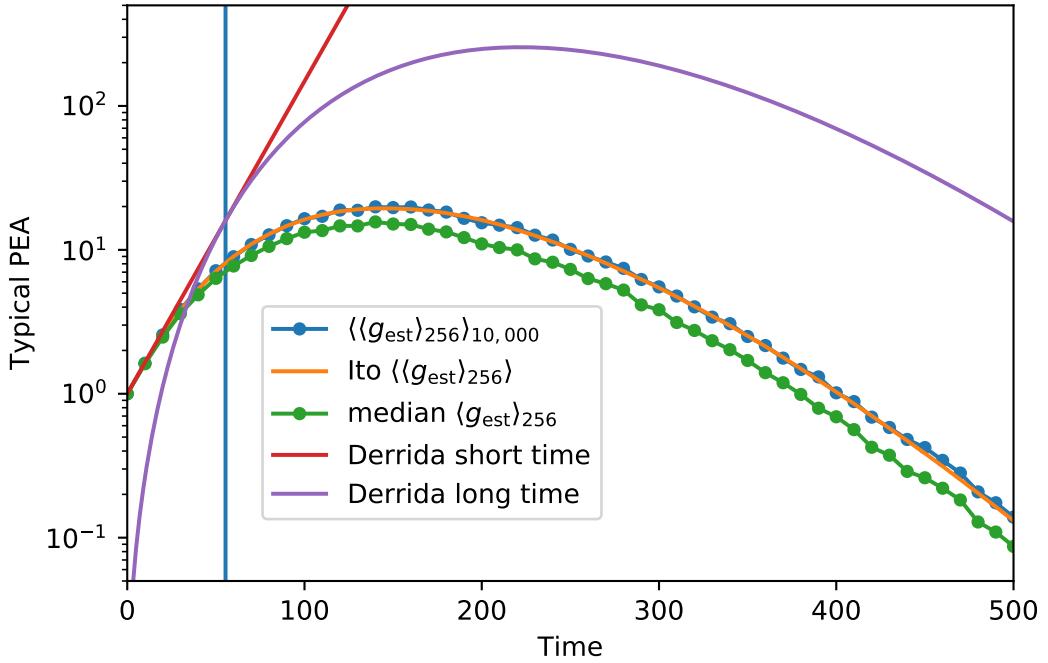


Figure 19: Lines are obtained by exponentiating the various exponential growth rates. **Blue line:** $\langle\langle g_{\text{est}} \rangle\rangle_{10,000}$ is the numerical mean (approximation of the expectation value) over a super-ensemble of $S = 10,000$ samples of g_{est} estimated in sub-ensembles of $N = 256$ GBMs each. **Green line:** median in a super-ensemble of S samples of g_{est} , each estimated in sub-ensembles of size N . **Yellow line:** An exact expression for $d\langle\ln\langle x\rangle_N\rangle$, derived using Itô calculus, see [?]. We evaluate the expression by Monte Carlo, and integrate, $\langle\ln\langle x\rangle_N\rangle = \int_0^t d\langle\ln\langle x\rangle_N\rangle$. Exponentiation yields the yellow line. **Red line:** short-time behavior, based on the random energy model, (Eq. 262). **Purple line:** long-time behavior, based on the random energy model, (Eq. 263). **Vertical line:** Crossover between the regimes at $t_c = \frac{2\ln N}{\sigma^2}$, corresponding to $\beta_c = \frac{2(\ln 2)^{1/2}}{\sigma}$. **Parameters:** $N = 256$, $S = 10,000$, $\mu = 0.05$, $\sigma = \sqrt{0.2}$.

4 Interactions

We add interactions to our null model of a population of noisy multipliers. It turns out that our decision criterion generates interesting emergent behaviour – cooperation, the sharing and pooling of resources, is often time-average growth optimal. This provides answers to the puzzles of why people cooperate and why we see socio-economic structure from the formation of firms to nation states with taxation and redistribution systems. We also ask whether assumptions about ergodicity in standard treatments of these topics are justified.

4.1 Cooperation

Under multiplicative growth, fluctuations are undesirable because they reduce time-average growth rates. In the long run, wealth $\mathbf{x}_1(t)$ with noise term σ_1 will outperform wealth $\mathbf{x}_2(t)$ with a larger noise term $\sigma_2 > \sigma_1$, in the sense that

$$\bar{g}(\mathbf{x}_1) > \bar{g}(\mathbf{x}_2) \quad (265)$$

with probability 1.

For this reason it is desirable to reduce fluctuations. One protocol that achieves this is pooling and sharing of resources. In Sec. 3.1 we explored the world created by the model of independent GBMs. This is a world where everyone experiences the same long-term growth rate. We want to explore the effect of the invention of cooperation. It turns out that cooperation increases growth rates, and this is a crucial insight.

Suppose two individuals, $\mathbf{x}_1(t)$ and $\mathbf{x}_2(t)$ decide to meet up every Monday, put all their wealth on a table, divide it in two equal amounts, and go back to their business (where their business is making their wealths follow GBM!) How would this operation affect the dynamic of the wealth of these two individuals?

Consider a discretised version of (Eq. 201), such as would be used in a numerical simulation. The non-cooperators grow according to

$$\Delta x_i(t) = \mathbf{x}_i(t) [\mu\Delta t + \sigma\sqrt{\Delta t}\xi_i], \quad (266)$$

$$\mathbf{x}_i(t + \Delta t) = \mathbf{x}_i(t) + \Delta x_i(t), \quad (267)$$

where ξ_i are standard normal random variates, $\xi_i \sim \mathcal{N}(0, 1)$.

We imagine that the two previously non-cooperating entities, with resources $\mathbf{x}_1(t)$ and $\mathbf{x}_2(t)$, cooperate to produce two entities, whose resources we label $\mathbf{x}_1^c(t)$ and $\mathbf{x}_2^c(t)$ to distinguish them from the non-cooperating case. We envisage equal sharing of resources, $\mathbf{x}_1^c = \mathbf{x}_2^c$, and introduce a cooperation operator, \oplus , such that

$$\mathbf{x}_1 \oplus \mathbf{x}_2 = \mathbf{x}_1^c + \mathbf{x}_2^c. \quad (268)$$

In the discrete-time picture, each time step involves a two-phase process. First there is a growth phase, analogous to (Eq. 201), in which each cooperator increases its resources by

$$\Delta x_i^c(t) = \mathbf{x}_i^c(t) [\mu\Delta t + \sigma\sqrt{\Delta t}\xi_i]. \quad (269)$$

This is followed by a cooperation phase, replacing (Eq. 267), in which resources are pooled and shared equally among the cooperators:

$$\mathbf{x}_i^c(t + \Delta t) = \frac{\mathbf{x}_1^c(t) + \Delta x_1^c(t) + \mathbf{x}_2^c(t) + \Delta x_2^c(t)}{2}. \quad (270)$$

With this prescription both cooperators and their sum experience the following dynamic:

$$(\mathbf{x}_1 \oplus \mathbf{x}_2)(t + \Delta t) = (\mathbf{x}_1 \oplus \mathbf{x}_2)(t) \left[1 + \left(\mu\Delta t + \sigma\sqrt{\Delta t} \frac{\xi_1 + \xi_2}{2} \right) \right]. \quad (271)$$

For ease of notation we define

$$\xi_{1\oplus2} = \frac{\xi_1 + \xi_2}{\sqrt{2}}, \quad (272)$$

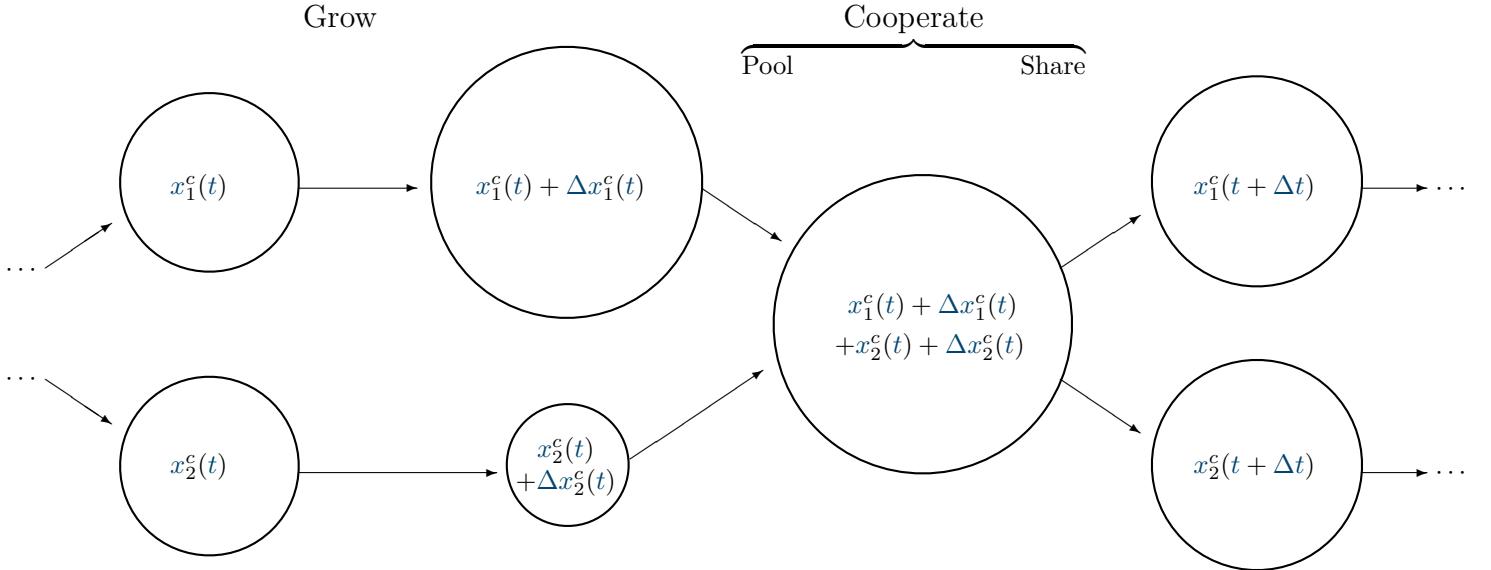


Figure 20: Cooperation dynamics. Cooperators start each time step with equal resources, then they *grow* independently according to (Eq. 269), then they *cooperate* by *pooling* resources and *sharing* them equally, then the next time step begins.

which is another standard Gaussian, $\xi_{1\oplus 2} \sim \mathcal{N}(0, 1)$. Letting the time increment $\Delta t \rightarrow 0$ we recover an equation of the same form as (Eq. 201) but with a different fluctuation amplitude,

$$d(\mathbf{x}_1 \oplus \mathbf{x}_2) = (\mathbf{x}_1 \oplus \mathbf{x}_2) \left(\mu dt + \frac{\sigma}{\sqrt{2}} dW_{1\oplus 2} \right). \quad (273)$$

The expectation values of a non-cooperator, $\langle \mathbf{x}_1(t) \rangle$, and a corresponding cooperator, $\langle \mathbf{x}_1^c(t) \rangle$, are identical. Based on expectation values, we thus cannot see any benefit of cooperation. Worse still, immediately after the growth phase, the better-off entity of a cooperating pair, $\mathbf{x}_1^c(t_0) > \mathbf{x}_2^c(t_0)$, say, would increase its expectation value from $\frac{\mathbf{x}_1^c(t_0) + \mathbf{x}_2^c(t_0)}{2} \exp(\mu(t - t_0))$ to $\mathbf{x}_1^c(t_0) \exp(\mu(t - t_0))$ by breaking the cooperation. But it would be foolish to act on the basis of this analysis: the short-term gain from breaking cooperation is a one-off, and is dwarfed by the long-term multiplicative advantage of continued cooperation. An analysis based on expectation values finds that there is no reason for cooperation to arise, and that if it does arise there are good reasons for it to end, *i.e.* it will be fragile. Because expectation values are inappropriately used to evaluate future prospects, the observation of widespread cooperation constitutes a conundrum.

The solution of the conundrum comes from considering the time-average growth rate. The non-cooperating entities grow at $g_t(\mathbf{x}_i) = \mu - \frac{\sigma^2}{2}$, whereas the cooperating unit benefits from a reduction of the amplitude of relative fluctuations and grows at $g_t(\mathbf{x}_1 \oplus \mathbf{x}_2) = \mu - \frac{\sigma^2}{4}$, and we have

$$g_t(\mathbf{x}_1 \oplus \mathbf{x}_2) > g_t(\mathbf{x}_i) \quad (274)$$

for any non-zero noise amplitude. Imagine a world where cooperation does not exist, just like in Sec. 3.1. Now introduce into this world two individuals who have invented cooperation – very quickly this pair of individuals will become vastly more wealthy than anyone else. To keep up, others will have to start cooperating. The effect is illustrated in Fig. 21 by direct simulation of (Eq. 266)–(Eq. 267) and (Eq. 271).

Imagine again the pair of cooperators outperforming all of their peers. Other entities will have to form pairs to keep up, and the obvious next step is for larger cooperating units to form – groups of 3 may form, pairs of pairs, cooperation clusters of N individuals, and the larger the cooperating group the closer the time-average growth rate will get to the expectation value. For N cooperators, $x_1 \oplus x_2 \dots \oplus x_N$ the spurious drift term is $-\frac{\sigma^2}{2N}$, so that the time-average growth approaches expectation-value growth for large N . The approach to this upper bound as the number of cooperators increases favours the formation of social structure.

We may generalise to different drift terms, μ_i , and noise amplitudes, σ_i , for different individual entities. Whether cooperation is beneficial in the long run for any given entity depends on these parameters as follows. Entity 1 will benefit from cooperation with entity 2 if

$$\mu_1 - \frac{\sigma_1^2}{2} < \frac{\mu_1 + \mu_2}{2} - \frac{\sigma_1^2 + \sigma_2^2}{8}. \quad (275)$$

We emphasize that this inequality may be satisfied also if the expectation value of entity 1 grows faster than the expectation value of entity 2, *i.e.* if $\mu_1 > \mu_2$. An analysis of expectation values, again, is utterly misleading: the benefit conferred on entity 1 due to the fluctuation-reducing effect of cooperation may outweigh the cost of having to cooperate with an entity with smaller expectation value.

We may also generalise to correlations between the fluctuations experienced by different entities. These are uncorrelated in our model: the dW_i in (Eq. 201) and, consequently, the ξ_i in (Eq. 266) onwards are independent random variables. In reality, cooperators are often spatially localised and experience similar environmental conditions. By allowing correlations between the ξ_i , our model can be adapted to describe such situations. This is more technically difficult and we won't present it here. If you are interested, you can find the details in [?].

Notice the nature of the Monte-Carlo simulation in Fig. 21. No ensemble is constructed. Only individual trajectories are simulated and run for a time that is long enough for statistically significant features to rise above the noise. This method teases out of the dynamics what happens over time. The significance of any observed structure – its epistemological meaning – is immediately clear: this is what happens over time for an individual system (a cell, a person's wealth, *etc.*). Simulating an ensemble and averaging over members to remove noise does not tell the same story. The resulting features may not emerge over time. They are what happens on average in an ensemble, but – at least for GBM – this is not what happens to the individual with probability 1. For instance the pink dashed line in Fig. 21 is the ensemble average of $x_1(t)$, $x_1(t)$, and $(x_1 \oplus x_2)(t)/2$, and it has nothing to do with what happens in the individual trajectories over time.

When judged on expectation values, the apparent futility of cooperation is unsurprising because expectation values are the result for infinitely many

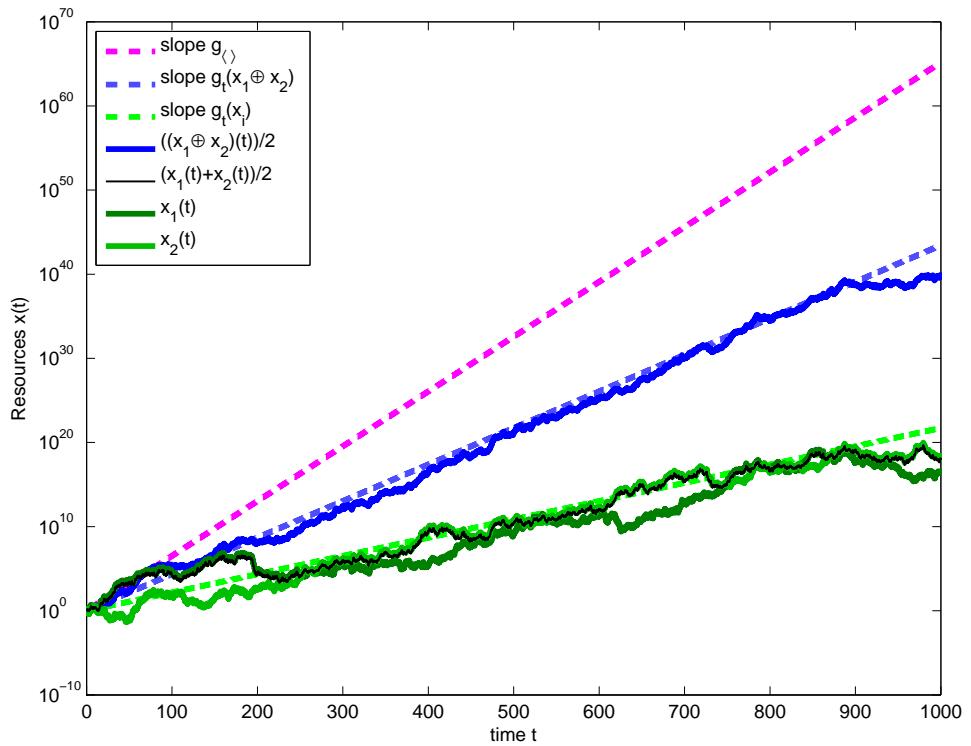


Figure 21: Typical trajectories for two non-cooperating (green) entities and for the corresponding cooperating unit (blue). Over time, the noise reduction for the cooperator leads to faster growth. Even without effects of specialisation or the emergence of new function, cooperation pays in the long run. The black thin line shows the average of the non-cooperating entities. While in the logarithmic vertical scale the average traces the more successful trajectory, it is far inferior to the cooperating unit. In a very literal mathematical sense the whole, $(\textcolor{teal}{x}_1 \oplus \textcolor{teal}{x}_2)(t)$, is more than the sum of its parts, $\textcolor{teal}{x}_1(t) + \textcolor{teal}{x}_2(t)$. The algebra of cooperation is not merely that of summation.

cooperators, and adding further cooperators cannot improve on this.

In our model the advantage of cooperation, and hence the emergence of social structure in the broadest sense – is purely a non-linear effect of fluctuations – cooperation reduces the magnitude of fluctuations, and over time (though not in expectation) this implies faster growth.

Another generalisation is partial cooperation – entities may share only a proportion of their resources, resembling taxation and redistribution. We discuss this in the next section.

4.2 Reallocation

4.2.1 Introduction

In Sec. 3.1 we created a model world of independent trajectories of **GBM**. We studied how the distribution of the resulting random variables evolved over time. We saw that this is a world of broadening distributions, increasing inequality, and wealth condensation.

We introduced cooperation to it in Sec. 4.1 and saw how this increases the time-average growth rate for those who pool and share all of their resources. In this section we study what happens if a large number of individuals pool and share only a fraction of their resources. This is reminiscent of the taxation and redistribution – which we shall call “reallocation” – carried out by populations in the real world.

We will find that, while full cooperation between two individuals increases their growth rates, sufficiently fast reallocation from richer to poorer in a large population has two related effects. Firstly, everyone’s wealth grows in the long run at a rate close to that of the expectation value. Secondly, the distribution of rescaled wealth converges over time to a stable form. This means that, while wealth can still be distributed quite unequally, wealth condensation and the divergence of inequality no longer occur in our model. Of course, for this to be an interesting finding, we will have to quantify what we mean by “sufficiently fast reallocation.”

We will also find that when reallocation is too slow or, in particular, when it goes from poorer to richer – which we will label negative reallocation – no stable wealth distribution exists. In the latter case, the population splits into groups with positive and negative wealths, whose magnitudes grow exponentially.

Finally, having understood how our model behaves in each of these reallocation regimes, we will fit the model parameters to historical wealth data from the real world, specifically the United States. This will tell us which type of model behaviour best describes the dynamics of the US wealth distribution in both the recent and more distant past. You might find the results surprising – we certainly did!

4.2.2 The ergodic hypothesis in economics

Of course, we are not the first to study resource distributions and inequality in economics. This topic has a long history, going back at least as far as Vilfredo Pareto’s work in the late 19th century [?] (in which he introduced the power-law distribution we discussed in Sec. 3.1.7). It’s worth spending a few moments considering how the subject is approached classically, before we say how we approach it.

Economists studying such distributions usually make the following assumption in their models: that the distributions converge in the long run to a unique and stable form, regardless of initial conditions. This allows them to study the stable distribution, for which many statistical techniques exist, and to ignore the transient phenomena preceding it, which are far harder to analyse. Paul Samuelson called this the “ergodic hypothesis” [?, pp. 11-12]. It’s easy to see why: if this convergence happens, then the time average of the observable under study will equal its ensemble average with respect to the stable distribution.²³

Economics is often concerned with growth and a growing quantity cannot be ergodic in Samuelson’s sense, because its distribution never stabilises. This suggests the simplifying ergodic hypothesis should *never* be made. Not so fast! Although rarely stated, a common strategy to salvage these techniques is to find a transformation of the non-ergodic process that produces a meaningful ergodic observable. If such an ergodic observable can be derived, then classical analytical techniques may still be used. We have already seen in the context of gambles that expected utility theory can be viewed as transformation of non-ergodic wealth increments into ergodic utility increments. Expectation values, which would otherwise be misleading, then quantify time-average growth of the decision-maker’s wealth.

Studies of wealth distributions also employ this strategy. Individual wealth is modelled as a growing quantity. Dividing by the population average transforms this to a rescaled wealth, as in Sec. 3.1.5, which is hypothesised to be ergodic. For example, [?, p. 130] “impose assumptions . . . that guarantee the existence and uniqueness of a limit stationary distribution.” The idea is to take advantage of the simplicity with which the stable distribution can be analysed, *e.g.* to predict the effects of policies encoded in model parameters.

There is, however, an elephant in the room. To our knowledge, the validity of the ergodic hypothesis for rescaled wealth has never been tested empirically. It’s certainly invalid for the GBM model world we studied previously because, as we saw in Sec. 3.1.5, rescaled wealth has an ever-broadening log-normal distribution. That doesn’t seem to say much, as most reasonable people would consider our model world – containing a population of individuals whose wealths multiply noisily and who never interact – a tad unrealistic. The model we are about to present will not only extend our understanding from this simple model world to one containing interactions, but also will allow us to test the hypothesis. This is because it has regimes, *i.e.* combinations of parameters, for which rescaled wealth is and isn’t ergodic. This contrasts with models typically used by economists, which have the ergodic hypothesis “baked in.”

If it is reasonable to assume a stable distribution exists, we must also consider how long convergence to would take after a change of parameters. It’s no use if convergence in the model takes the whole of human history, if we are using it to estimate the effect of a tax policy over the next election cycle. Therefore, treating a stable model distribution as representative of an empirical wealth distribution implies an assumption of fast convergence. As the late Tony Atkinson pointed out, “the speed of convergence makes a great deal of difference to the way in which we think about the model” [?]. We will use our model to discuss this point. Without further ado, let us introduce it.

²³Convergence to a unique and stable distribution is a sufficient but not necessary condition for an ergodic observable, as we have defined it.

4.2.3 Reallocating geometric Brownian motion

Our model, called **Reallocating geometric Brownian motion (RGBM)**, is a system of N individuals whose wealths, $x_i(t)$, evolve according to the stochastic differential equation,

$$dx_i = x_i [(\mu - \varphi)dt + \sigma dW_i(t)] + \varphi \langle x \rangle_N dt, \quad (276)$$

for $i = 1 \dots N$. In effect, we have added to **GBM** a simple reallocation mechanism. Over a time step, dt , each individual pays a fixed proportion of its wealth, $\varphi x_i dt$, into a central pot (“contributes to society”) and gets back an equal share of the pot, $\varphi \langle x \rangle_N dt$, (“benefits from society”). We can think of this as applying a wealth tax, say of 1% per year, to everyone’s wealth and then redistributing the tax revenues equally. Note that the reallocation parameter, φ , is, like μ , a rate with dimensions per unit time. Note also that when $\varphi = 0$, we recover our old friend, **GBM**, in which individuals grow their wealths without interacting.

RGBM is our null model of an exponentially growing economy with social structure. It is intended to capture only the most general features of the dynamics of wealth. A more complex model would treat the economy as a system of agents that interact with each other through a network of relationships. These relationships include trade in goods and services, employment, taxation, welfare payments, using public infrastructure (roads, schools, a legal system, social security, scientific research, and so on), insurance, wealth transfers through inheritance and gifts, and so on. It would be a hopeless task to list exhaustively all these interactions, let alone model them explicitly. Instead we introduce a single parameter – the reallocation rate, φ – to represent their net effect. If φ is positive, the direction of net reallocation is from richer to poorer. If negative, it is from poorer to richer.

We will see shortly that **RGBM** has both ergodic and non-ergodic regimes, characterised to a good approximation by the sign of φ . $\varphi > 0$ produces an ergodic regime, in which wealths are positive, distributed with a Pareto tail, and confined around their mean value. $\varphi < 0$ produces a non-ergodic regime, in which the population splits into two classes, characterised by positive and negative wealths which diverge away from the mean.

We offer a couple of health warnings. In **RGBM**, like in **GBM**, there are no additive changes akin to labour income and consumption. This is unproblematic for large wealths, where additive changes are dwarfed by capital gains. For small wealths, however, wages and consumption are significant and empirical distributions look rather different for low and high wealths [?]. We modelled earnings explicitly in [?] and found this didn’t generate insights different from **RGBM** when we fit both models to real wealth data. We note also, as [?, p. 41] put it, that our agents “do not marry or have children or die or even grow old.” Therefore, the individual in our setup is best imagined as a household or a family, *i.e.* some long-lasting unit into which personal events are subsumed.

Having specified the model, we will use insights from Sec. 3.2 to understand how rescaled wealth is distributed in the ergodic and non-ergodic regimes. Then we will show briefly our results from fitting the model to historical wealth data from the United States. The full technical details of this fitting exercise are beyond the scope of these notes – if you are interested, you can find “chapter and verse” in [?]. Fitting φ to data will allow us to answer the important questions:

- What is the net reallocating effect of socio-economic structure on the wealth distribution?
- Are observations consistent with the ergodic hypothesis that the rescaled wealth distribution converges to a stable distribution?
- If so, how long does it take, after a change in conditions, for the rescaled wealth distribution to reach the stable distribution?

4.2.4 Model behaviour

It is instructive to write (Eq. 276) as

$$dx_i = \underbrace{x_i [\mu dt + \sigma dW_i(t)]}_{\text{Growth}} - \underbrace{\varphi(x_i - \langle x \rangle_N) dt}_{\text{Reallocation}}. \quad (277)$$

This resembles **GBM** with a mean-reverting term like that of [?] in physics and [?] in finance. It exposes the importance of the sign of φ . We discuss the two regimes in turn.

Positive φ

For $\varphi > 0$, individual wealth, $x_i(t)$, reverts to the sample mean, $\langle x(t) \rangle_N$. We explored some of the properties of sample mean in Sec. 3.2 for wealths undergoing **GBM**. In particular, we saw that a short-time (or large-sample or low-volatility) self-averaging regime exists, (Eq. 257) $t < t_c \equiv \frac{2 \ln N}{\sigma^2}$, where the sample mean is approximated well by the ensemble average,

$$\langle x(t) \rangle_N \sim \langle x(t) \rangle = \exp(\mu t). \quad (278)$$

(The final equality assumes, as previously, that $x_i(0) = 1$ for all i .) It turns out that the same self-averaging approximation can be made for wealths undergoing **RGBM**, (Eq. 276), when the reallocation rate, φ , is above some critical threshold:

$$\varphi > \varphi_c \equiv \frac{\sigma^2}{2 \ln N}. \quad (279)$$

Showing this is technically difficult [?] and we will confine ourselves to sketching the key ideas in Sec. 4.2.5 below. It won't have escaped your attention that $\varphi_c = t_c^{-1}$ and, indeed, you will shortly have an intuition for why.

Fitting the model to data yields parameter values for which φ_c is extremely small. For example, typical parameters for US wealth data are $N = 10^8$ and $\sigma = 0.2 \text{ year}^{-1/2}$, giving $\varphi_c = 0.1\% \text{ year}^{-1}$ (or $t_c = 900$ years). Accounting for the uncertainty in the fitted parameters makes this statistically indistinguishable from $\varphi_c = 0$.

This means we can safely make the self-averaging approximation for the entire positive φ regime. That's great news, because it means we can rescale wealth by the ensemble average, $\langle x(t) \rangle = \exp(\mu t)$, as we did in Sec. 3.1.5 for **GBM**, and not have to worry about pesky finite N effects. Following the same procedure as there gives us a simple SDE in the rescaled wealth, $y_i(t) = x_i(t) \exp(-\mu t)$:

$$dy_i = y_i \sigma dW_i(t) - \varphi(y_i - 1) dt. \quad (280)$$

Note that the common growth rate, μ , has been scaled out as it was in Sec. 3.1.5.

The distribution of $y_i(t)$ can be found by solving the corresponding Fokker-Planck equation, which we will do in Sec. 4.2.5. For now, we will just quote the result: a stable distribution exists with a power-law tail, to which the distribution of rescaled wealth converges over time. The distribution has a name – the Inverse Gamma Distribution – and a probability density function:

$$\mathcal{P}(y) = \frac{(\zeta - 1)^\zeta}{\Gamma(\zeta)} e^{-\frac{\zeta-1}{y}} y^{-(1+\zeta)}. \quad (281)$$

$\zeta = 1 + 2\varphi/\sigma^2$ is the Pareto tail index (corresponding to $\alpha - 1$ in Sec. 3.1.7) and $\Gamma(\cdot)$ is the gamma function.

Example forms of the stationary distribution are shown in Figure 22. The usual stylised facts are recovered: the larger σ (more randomness in the returns) and the smaller φ (less social cohesion), the smaller the tail index ζ and the fatter the tail of the distribution. Fitted φ values give typical ζ values between 1 and 2 for the different datasets analysed, consistent with observed tail indices between 1.2 to 1.6 (see [?] for details). Not only does RGBM predict a realistic functional form for the distribution of rescaled wealth, but also it admits fitted parameter values which match observed tails. The inability to do this is a known weakness of earnings-based models (again, see [?] for discussion).

For positive reallocation, (Eq. 280) and extensions of it have received much attention in statistical mechanics and econophysics [?, ?]. As a combination of GBM and a mean-reverting process it is a simple and analytically tractable stochastic process. [?] provide an overview of the literature and known results.

Negative φ

For $\varphi < 0$ the model exhibits mean repulsion rather than reversion. The ergodic hypothesis is invalid and no stationary wealth distribution exists. The population splits into those above the mean and those below the mean. Whereas in RGBM with non-negative φ it is impossible for wealth to become negative, negative φ leads to negative wealth. No longer is total economic wealth a limit to the wealth of the richest individual because the poorest develop large negative wealth. The wealth of the rich in the population increases exponentially away from the mean, and the wealth of the poor becomes negative and exponentially large in magnitude, see Figure 23.

Such splitting of the population is a common feature of non-ergodic processes. If rescaled wealth were an ergodic process, then individuals would, over long enough time, experience all parts of its distribution. People would spend 99 percent of their time as “the 99 percent” and 1 percent of their time as “the 1 percent”. Therefore, the social mobility implicit in models that assume ergodicity might not exist in reality if that assumption is invalid. That inequality and immobility have been linked [?, ?, ?] may be unsurprising if both are viewed as consequences of non-ergodic wealth or income.

4.2.5 Derivation of the stable distribution

In this section we will sketch the argument for why we can make the self-averaging approximation, (Eq. 278), in RGBM with sufficiently fast positive reallocation, (Eq. 279). This is shown rigorously in [?]. Then we will solve the Fokker-Planck equation for the rescaled wealth and derive the inverse gamma distribution, (Eq. 281).

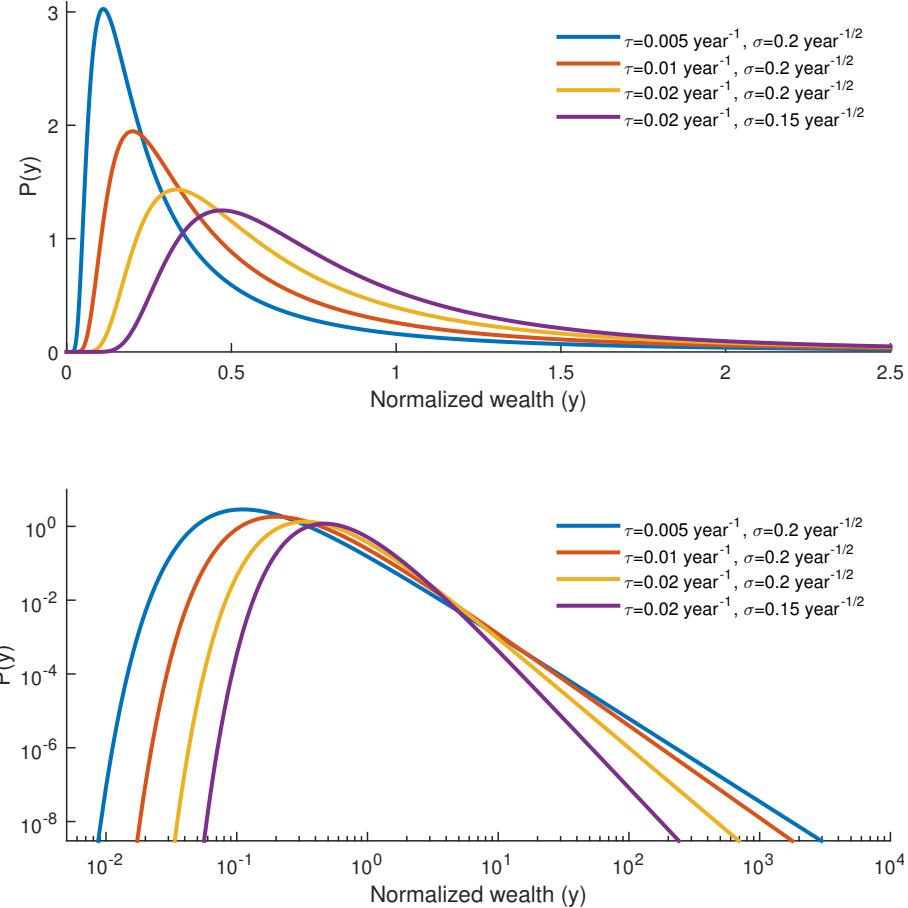


Figure 22: The stationary distribution for **RGBM** with positive φ . Top – linear scales; Bottom – logarithmic scales.

We presented arguments in Sec. 3.2.1 for why wealth in **GBM** is self-averaging, $\langle x(t) \rangle_N \sim \langle x(t) \rangle = \exp(\mu t)$ for short time. By mapping from **GBM** to the random energy model in Sec. 3.2.2, we showed that “short time” means $t < t_c$, where $t_c = 2 \ln N/\sigma^2$. We can think of this as follows: t_c is the timescale over which the inequality-increasing effects of noisy multiplicative growth drive wealths apart, such that a finite sample of wealths stops self-averaging and becomes dominated by a few trajectories.

Let’s now think about what happens when we add reallocation to **GBM**, creating **RGBM**. φ is the reallocation rate, so φ^{-1} is reallocation timescale, *i.e.* the timescale over which the inequality-reducing effects of reallocation pull wealths together. If $\varphi^{-1} > t_c$, then reallocation happens too slowly to prevent the expiry of self-averaging. However, if $\varphi^{-1} < t_c$, then reallocation pulls wealths together more quickly than they get driven apart, continually “resetting” the sample and allowing self-averaging to be maintained indefinitely. Converting this condition into a reallocation rate, we get $\varphi > t_c^{-1}$, as in (Eq. 279). As mentioned in Sec. 4.2.4, this becomes indistinguishable from $\varphi > 0$ for realistic parameters,

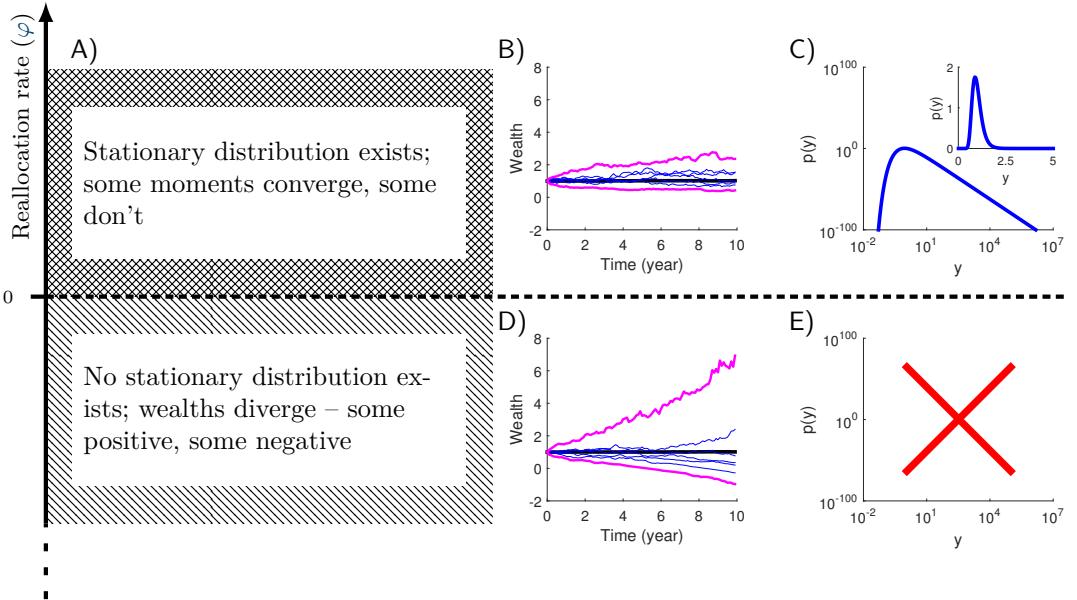


Figure 23: Regimes of **RGBM**. A) $\varphi = 0$ separates the two regimes of **RGBM**. For $\varphi > 0$, a stationary wealth distribution exists. For $\varphi < 0$, no stationary wealth distribution exists and wealths diverge. B) Simulations of **RGBM** with $N = 1000$, $\mu = 0.021 \text{ year}^{-1}$ (presented after rescaling by $\exp(\mu t)$), $\sigma = 0.14 \text{ year}^{-1/2}$, $x_i(0) = 1$, $\varphi = 0.15 \text{ year}^{-1}$. Magenta lines: largest and smallest wealths, blue lines: five randomly chosen wealth trajectories, black line: sample mean. C) The stationary distribution to which the system in B) converges. Inset: same distribution on linear scales. D) Similar to B), with $\varphi = -0.15 \text{ year}^{-1}$. E) in the $\varphi < 0$ regime, no stationary wealth distribution exists.

so the self-averaging approximation can be made safely for all positive φ when using the model to study real economies.

We can now approximate the rescaled wealth, $y_i(t) = x_i(t)/\langle x(t) \rangle_N$, as $y_i(t) = x_i(t)\exp(-\mu t)$. Using Itô's formula as we did Sec. 3.1.5 yields the following SDE for rescaled wealth, now under **RGBM** instead of **GBM**:

$$dy = \sigma y dW - \varphi(y - 1) dt. \quad (282)$$

This is an Itô equation with drift term $A = \varphi(y - 1)$ and diffusion term $B = y\sigma$. Such equations imply ordinary second-order differential equations that describe the evolution of the **PDF**, called Fokker-Planck equations. The Fokker-Planck equation describes the change in probability density, at any point in (rescaled wealth) space, due to the action of the drift term (like advection in a fluid) and due to the diffusion term (like heat spreading). In this case, we have

$$\frac{d\mathcal{P}(y, t)}{dt} = \frac{\partial}{\partial y} [A\mathcal{P}(y, t)] + \frac{1}{2} \frac{\partial^2}{\partial y^2} [B^2 \mathcal{P}(y, t)]. \quad (283)$$

The steady-state Fokker-Planck equation for the **PDF**, $\mathcal{P}(y)$, is obtained by

setting the time derivative to zero,

$$\frac{\sigma^2}{2} (y^2 \mathcal{P})_{yy} + \varphi [(y - 1) \mathcal{P}]_y = 0. \quad (284)$$

Positive wealth subjected to continuous-time multiplicative dynamics with non-negative reallocation can never reach zero. Therefore, we solve Equation (284) with boundary condition $\mathcal{P}(0) = 0$ to give

$$\mathcal{P}(y) = C(\zeta) e^{-\frac{\zeta-1}{y}} y^{-(1+\zeta)}, \quad (285)$$

where

$$\zeta = 1 + \frac{2\varphi}{\sigma^2} \quad (286)$$

and

$$C(\zeta) = \frac{(\zeta - 1)^\zeta}{\Gamma(\zeta)}, \quad (287)$$

with the gamma function $\Gamma(\zeta) = \int_0^\infty x^{\zeta-1} e^{-x} dx$. The distribution has a power-law tail as $y \rightarrow \infty$, resembling Pareto's oft-confirmed observation that the frequency of large wealths tends to decay as a power-law [?]. The exponent of the power-law, ζ , is called the Pareto parameter and is one measure of economic inequality.

4.2.6 Moments and convergence times

The inverse gamma distribution, (Eq. 281), has a power-law tail. This means that, for positive reallocation, while some of the lower moments of the stable rescaled wealth distribution may exist, higher moments will not. Specifically, the k^{th} moment diverges if $k > \zeta$.

If we find parameters consistent with positive reallocation when we fit our model to data, we will be interested in whether certain statistics – such as the variance – exist. We will also want to know how long it takes the distribution to converge sufficiently to its stable form for them to be meaningful. Here we derive a condition for the convergence of the variance and calculate its convergence time, noting also the general procedure for other statistics.

The variance of y is a combination of the first moment, $\langle y \rangle$ (the ensemble average), and the second moment, $\langle y^2 \rangle$:

$$V(y) = \langle y^2 \rangle - \langle y \rangle^2 \quad (288)$$

Thus we need to find $\langle y \rangle$ and $\langle y^2 \rangle$ in order to determine the variance.

The first moment of the rescaled wealth is, by definition, $\langle y \rangle = 1$. To find the dynamic of the second moment, we start with the SDE for the rescaled wealth,

$$dy = \sigma y dW - \varphi (y - 1) dt, \quad (289)$$

and follow a now familiar procedure. We insert $f(y, t) = y^2$ into Itô's formula,

$$df = \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial y} dy + \frac{1}{2} \frac{\partial^2 f}{\partial y^2} dy^2 \quad (290)$$

to obtain

$$d(y^2) = 2y dy + dy^2. \quad (291)$$

We substitute (Eq. 291) for dy to get terms at orders dW , dt , dW^2 , dt^2 , and $dWdt$. The scaling of **BM** allows us to replace dW^2 by dt and we ignore terms at $o(dt)$. This yields

$$d(y^2) = 2\sigma y^2 dW - (2\varphi - \sigma^2) y^2 dt + 2\varphi y dt. \quad (292)$$

Taking expectations on both sides and noting that $\langle y \rangle = 1$ gives us an ordinary differential equation for the second moment:

$$\frac{d\langle y^2 \rangle}{dt} = - (2\varphi - \sigma^2) \langle y^2 \rangle + 2\varphi \quad (293)$$

with solution

$$\langle y(t)^2 \rangle = \frac{2\varphi}{2\varphi - \sigma^2} + \left(\langle y(0)^2 \rangle - \frac{2\varphi}{2\varphi - \sigma^2} \right) e^{-(2\varphi - \sigma^2)t}. \quad (294)$$

The variance $V(t) = \langle y(t)^2 \rangle - 1$ therefore follows

$$V(t) = V_\infty + (V_0 - V_\infty) e^{-(2\varphi - \sigma^2)t}, \quad (295)$$

where V_0 is the initial variance and

$$V_\infty = \frac{2\varphi}{2\varphi - \sigma^2}. \quad (296)$$

V converges in time to the asymptote, V_∞ , provided the exponential in (Eq. 295) is decaying. This can be expressed as a condition on φ

$$\varphi > \frac{\sigma^2}{2}, \quad (297)$$

which is the same as the condition we noted previously for the second moment to exist: $\zeta > k$ where $k = 2$.

Clearly, for negative values of φ the condition cannot be satisfied, and the variance (and inequality) of the wealth distribution will diverge. In the regime where the variance exists, $\varphi > \sigma^2/2$, it also follows from (Eq. 295) that the convergence time of the variance is $1/(2\varphi - \sigma^2)$.

As φ increases, increasingly high moments of the distribution converge to finite values. The above procedure for finding the second moment (and thereby the variance) can be applied to the k^{th} moment, just by changing the second power y^2 to y^k . Therefore, any other cumulant can be found as a combination of the relevant moments. For instance, [?] also compute the third cumulant.

4.2.7 Fitting United States wealth data

We have introduced the **RGBM** model and understood its basic properties. It is a simple model of an interacting population of noisy multiplicative growers. We expect it to be more realistic than **GBM** ($\varphi = 0$) because we know that in the real world people interact. In particular, large populations have over centuries developed public institutions and infrastructure, to which everyone contributes and from which everyone benefits. At first glance, therefore, we might expect

to find that **RGBM** with positive φ to fit real wealth data better than **GBM** or, indeed, **RGBM** with negative φ .

Additionally, if this is true and if associated convergence times are shorter than the timescales of policy changes, it would indicate that the ergodic hypothesis is warranted and a helpful modelling assumption. If not, then the hypothesis would be unjustified and could be acting as a serious constraint on models of economic inequality, generating misleading analyses and recommendations.

In [?] we fit the **RGBM** model to historical wealth data from the United States for the last hundred years. We won't include full technical description of this empirical analysis here. It would be too long and our main aim is to communicate the ideas we use to think about problems and build models. If you want to know more, please read the paper (and let us know what you think!) However, the results are interesting and, to us at least, a little shocking, so we include a brief summary.

The basic setup is to fix the values of μ , σ , and N in our **RGBM** model using data about, respectively, aggregate economic growth, stock market volatility, and population data; and then to find, by numerical simulation of (Eq. 276), the time series of $\varphi(t)$ values which best reproduces historical wealth shares in the United States. The wealth share, $S_q(t)$, is a type of inequality measure. It is defined as the proportion of total wealth owned by the richest fraction q of the population. So, for example, $S_{0.1} = 0.8$ means that the richest 10% of the population own 80% of the total wealth. Reproducing the historical wealth shares is one way of reproducing approximately the level of inequality in the wealth distribution, and the nice thing is that economists Emmanuel Saez and Gabriel Zucman have estimated around a century's worth of wealth shares for the United States [?].

Fitting the model to these data will address two main questions:

- Is the ergodic hypothesis valid for rescaled wealth in the United States? For it to be valid, fitted values of $\varphi(t)$ must be robustly positive.
- If $\varphi(t)$ is robustly positive, is convergence of the distribution to its stable form fast enough for the distribution to be used as a representative of the empirical wealth distribution?

Note that we have relaxed the model slightly. φ is a fixed parameter in (Eq. 276) but we allow it to vary with time in our empirical analysis.

Figure 24 (top) shows the results of fitting the **RGBM** model to the wealth share data in [?]. There are large annual fluctuations in $\varphi_q(t)$ (black line) but we are more interested in longer-term changes in reallocation driven by structural economic and political changes. To show these, we smooth the data by taking a central 10-year moving average, $\tilde{\varphi}_q(t)$ (red line), where the window is truncated at the ends of the time series. We also show the uncertainty in this moving average (red envelope).

To ensure the smoothing does not introduce artificial biases, we reverse the procedure and use $\tilde{\varphi}_q(t)$ to propagate the initially inverse gamma-distributed wealths and determine the wealth shares $S_q^{\text{model}}(t)$. The good agreement with $S_q^{\text{data}}(t)$ suggests that the smoothed $\tilde{\varphi}_q(t)$ is meaningful, see Figure 24 (bottom).

The “take home” is this: while the effective reallocation rate, $\tilde{\varphi}(t)$, was positive for most of the last hundred years, it was negative – *i.e.* reallocation from

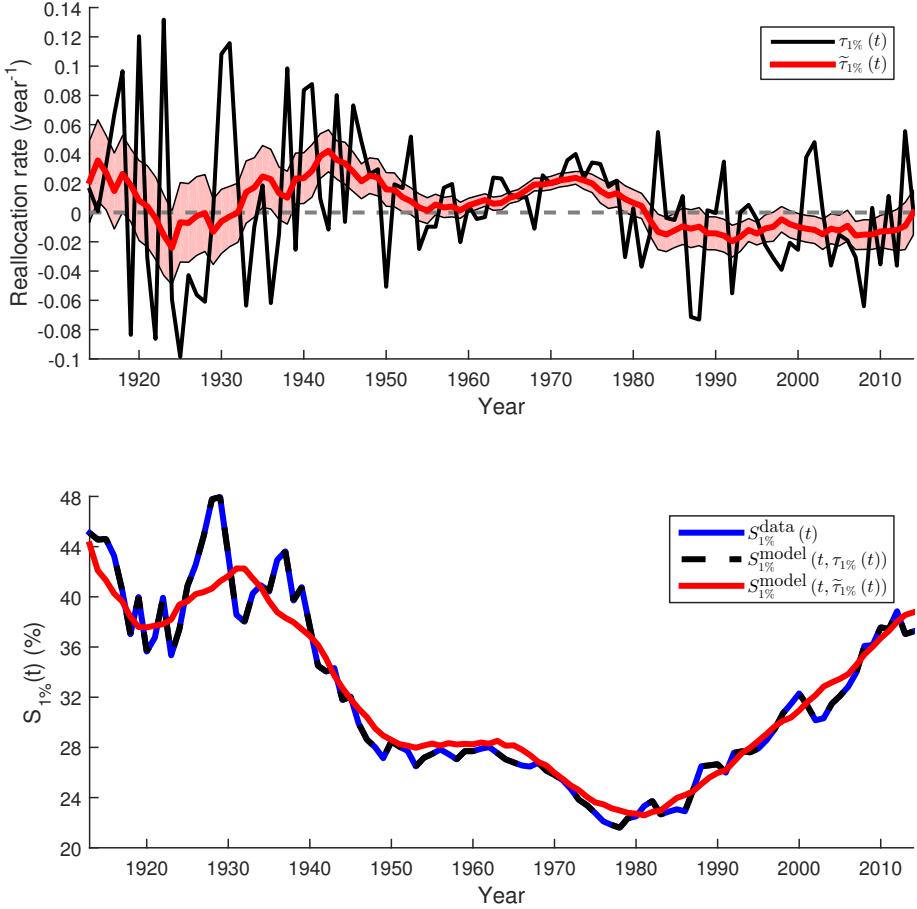


Figure 24: Fitted effective reallocation rates. Calculations done using $\mu = 0.021 \text{ year}^{-1}$ and $\sigma = 0.16 \text{ year}^{-1/2}$. Top: $\varphi_{1\%}(t)$ (black) and $\tilde{\varphi}_{1\%}(t)$ (red). Translucent envelopes indicate one standard error in the moving averages. Bottom: $S_{1\%}^{\text{data}}$ (blue), $S_{1\%}^{\text{model}}$ based on the annual $\varphi_{1\%}(t)$ (dashed black), based on the 10-year moving average $\tilde{\varphi}_{1\%}(t)$ (red).

poorer to richer – from the mid-1980s onwards. Furthermore, even when $\varphi(t)$ was positive, associated convergence times (estimated both by numerical simulation and by plugging fitted model parameters into the results of Sec. 4.2.6) were very long compared to the typical times between policy changes – from several decades to several centuries. This makes the answer to both our questions above a resounding “No.”

What shocked us most when we first encountered these results was the existence of long periods with negative reallocation. We began the analysis imagining that GBM (*i.e.* $\varphi = 0$, no interactions) was a really crazy model of the real world. After all, we personally pay our taxes and use public services, and the London Mathematical Laboratory is supported by generous charitable reallocations! We imagined that we would see $\varphi > 0$ but that it might be so small that convergence times would be too long for the ergodic hypothesis to be useful. In-

stead we found that, recently in the United States at least, reallocation has been consistently negative. In our model, this corresponds to wealths being driven apart, populations splitting into groups with positive and negative wealths, and no convergence to a stable distribution of rescaled wealth.

In retrospect, perhaps we shouldn't have been so surprised. Qualitatively, our results echo the findings that the rich are experiencing higher growth rates of their wealth than the poor [?, ?] and that the cumulative wealth of the poorest 50 percent of the American population was negative during 2008–2013 [?, ?].

The economic phenomena that trouble theorists most – such as diverging inequality, social immobility, and the emergence of negative wealth – are difficult to reproduce in models that make the ergodic hypothesis. In our simple model, this is easy to see: in the ergodic regime, $\varphi > 0$, our model cannot reproduce these phenomena at all. One may be tempted to conclude that their existence is a sign of special conditions prevailing in the real world – collusion and conspiracies. But if we admit the possibility of non-ergodicity, $\varphi \leq 0$, it becomes clear that these phenomena can easily emerge in an economy that does not actively guard against them.

5 Markets

This lecture applies the ideas developed in the first two lectures to markets.

We set up a simple portfolio selection problem in a market of two assets: one risky, like shares; and the other riskless, like a bank deposit. We ask how an investor would best allocate his money between the two assets, which we phrase in terms of his leverage. We review the classical approach, which can't answer this question without additional information about the investor's risk preferences. We then use the decision theory we've developed so far to answer the question unambiguously, by deriving the optimal leverage which maximises the investment's time-average growth rate.

This is a Gedankenexperiment that will lead us to predict and the empirically discover certain regularities in the price statistics of freely traded assets. We consider what this objectively defined optimal leverage might mean for financial markets themselves. If all the participants in a market aim for the same optimal leverage, does this constrain the prices and price fluctuations that emerge from their trading? We argue that it does, and we quantify how. Our treatment of the problem generates a theory of noise in stock prices, resolves the so-called equity premium puzzle (and the price volatility puzzle), provides a natural framework for setting central-bank interest rates, and even suggests a method for fraud detection. We test our predictions using data collected from the American and German stock markets as well as Bitcoin and Bernie Madoff's Ponzi scheme.

5.1 Optimal leverage

5.1.1 A model market

We consider assets whose values follow multiplicative dynamics, which we will model using **GBM**. In general, an amount x invested in such an asset evolves according to the **SDE**,

$$dx = x(\mu dt + \sigma dW), \quad (298)$$

where μ is the drift and σ is the volatility. By now we are very familiar with this equation and how to solve it.

To keep things simple, we imagine a market of two assets. One asset is riskless: the growth in its value is known deterministically and comes with a cast-iron guarantee.²⁴ This might correspond in reality to a bank deposit. The other asset is risky: there is uncertainty over what its value will be in the future. This might correspond to a share in a company or a collection of shares in different companies. We will think of it simply as stock.

An amount x_0 invested in the riskless asset evolves according to

$$dx_0 = x_0\mu_r dt. \quad (299)$$

μ_r is the riskless drift, known in finance as the riskless rate of return.²⁵ There is no volatility term. In effect, we have set $\sigma = 0$. We know with certainty what x_0 will be at any point in the future:

$$x_0(t_0 + \Delta t) = x_0(t_0) \exp(\mu_r \Delta t). \quad (300)$$

An amount x_1 invested in the risky asset evolves according to

$$dx_1 = x_1(\mu_s dt + \sigma_s dW), \quad (301)$$

where $\mu_s > \mu_r$ is the risky drift and $\sigma_s > 0$ is the volatility (the subscript s stands for stock). μ_s is also known in finance as the expected return.²⁶ This equation has solution

$$x_1(t_0 + \Delta t) = x_1(t_0) \exp \left[\left(\mu_s - \frac{\sigma_s^2}{2} \right) \Delta t + \sigma_s W(\Delta t) \right], \quad (302)$$

which is a random variable.

We will refer to the difference

$$\mu_e = \mu_s - \mu_r \quad (303)$$

as the excess drift.

²⁴Such guarantees are easy to offer in a model. In the real world, one should be very suspicious of anything that comes with a “cast-iron guarantee”.

²⁵In general we will eschew financial terminology for rates. Economics has failed to define them clearly, with the result that different quantities, like \bar{g} and $g_{\langle \rangle}$, are often conflated. The definitions developed in these lectures are aimed at avoiding such confusion.

²⁶Probably because it’s the growth rate of the expected value, see (Eq. 310).

5.1.2 Leverage

Let's turn to the concept of leverage. Imagine a very simple portfolio of value x_ℓ , out of which ℓx_ℓ is invested in stock and the remainder, $(1 - \ell)x_\ell$, is put in the bank. ℓ is known as the leverage. It is the fraction of the total investment assigned to the risky asset. $\ell = 0$ corresponds to a portfolio consisting only of bank deposits. $\ell = 1$ corresponds to a portfolio only of stock.

You would be forgiven for thinking that prudence dictates $0 \leq \ell \leq 1$, *i.e.* that we invest some of our money in stock and keep the rest in the bank. However, the financial markets have found all sorts of exciting ways for us to invest almost any amount in an asset. For example, we can make $\ell > 1$ by borrowing money from the bank to buy more stock than we could have bought with only our own money.²⁷ We can even make $\ell < 0$ by borrowing stock (a negative investment in the risky asset), selling it, and putting the money raised in the bank. In the financial world this practice is called short selling.

Each investment in our portfolio experiences the same relative fluctuations as the asset in which it has been made. The overall change in the portfolio's value is, therefore,

$$dx_\ell = (1 - \ell)x_\ell \frac{dx_0}{x_0} + \ell x_\ell \frac{dx_1}{x_1}. \quad (304)$$

Substituting in (Eq. 299) and (Eq. 301) gives the SDE for a leveraged investment in the risky asset,

$$dx_\ell = x_\ell [(\mu_r + \ell \mu_e)dt + \ell \sigma_s dW], \quad (305)$$

with solution,

$$x_\ell(t_0 + \Delta t) = x_\ell(t_0) \exp \left[\left(\mu_r + \ell \mu_e - \frac{\ell^2 \sigma_s^2}{2} \right) \Delta t + \ell \sigma_s W(\Delta t) \right]. \quad (306)$$

We can now see why we labelled investments in the riskless and risky assets by x_0 and x_1 : when $\ell = 0$, x_ℓ follows the same evolution as x_0 ; and when $\ell = 1$, it evolves as x_1 .

In our model ℓ , once chosen, is held constant over time. This means that our model portfolio must be continuously rebalanced to ensure that the ratio of stock to total investment stays fixed at ℓ . For example, imagine our stock investment fluctuates up a lot over a short time-step, while our bank deposit only accrues a little interest. Immediately we have slightly more than ℓ of the portfolio's value in stock, and slightly less than $1 - \ell$ of its value in the bank. To return the leverage to ℓ , we need to sell some stock and deposit the proceeds in the bank, Fig. 25. In (Eq. 305) we are imagining that this happens continuously.²⁸

5.1.3 Portfolio theory

Our simple model portfolio parametrised by ℓ allows us to ask the

²⁷This doesn't immediately affect the portfolio's value. The bank loan constitutes a negative investment in the riskless asset, whose value cancels the value of the stock we bought with it. Of course, the change in the portfolio's composition will affect its future value.

²⁸In reality, of course, that's not possible. We could try to get close by rebalancing frequently. However, every time we buy or sell an asset in a real market, we pay transaction costs, such as broker's fees and transaction taxes. This means that frequent rebalancing in the real world can be costly.

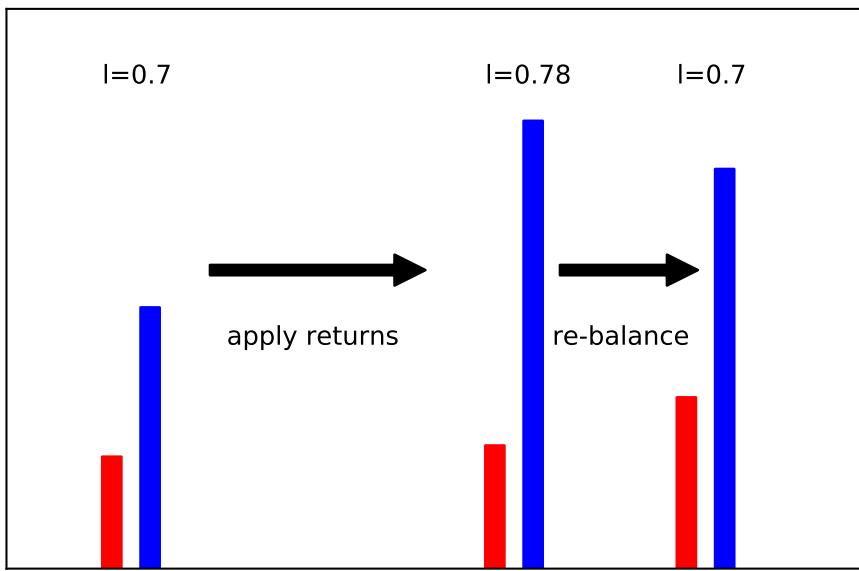


Figure 25: Investment in a risky (blue) and riskless (red) asset. Leverage starts at $\ell = 0.7$, meaning 70% is invested in the risky asset, and 30% in the riskless. The investment then experiences the relative returns of the market. In this case the risky asset goes up quite a bit, and the riskless asset goes up less. Consequently, the leverage changes. To maintain a constant leverage, some risky asset has to be sold in return for some riskless, a step known as re-balancing.

Question:

What is the optimal value of ℓ ?

This is similar to choosing between gambles, for which we have already developed a decision theory. The main difference is that we are now choosing from a continuum of gambles, each characterised by a value of ℓ , whereas previously we were choosing between discrete gambles. The principle, however, is the same: we will maximise the time-average growth rate of our investment.

Before we do this, let's review the classical treatment of the problem so that we appreciate the wider context. Intuitively, people understand there is some kind of trade-off between risk and reward. In our model of a generic multiplicative asset, (Eq. 298), we could use σ as a proxy for risk and μ as a proxy for reward. Ideally we want an investment with large μ and small σ , but we also acknowledge the rule-of-thumb that assets with larger μ tend to have larger σ .²⁹ This is why we model our risky asset as having a positive excess return, $\mu_e > 0$, over the riskless asset.

Intuition will only take us so far. A rigorous treatment of the portfolio selection problem was first attempted by Markowitz in 1952 [?]. He suggested defining a portfolio with parameters (σ_i, μ_i) as efficient if there exists no rival portfolio with parameters (σ_j, μ_j) with $\mu_j \geq \mu_i$ and $\sigma_j \leq \sigma_i$. Markowitz argued that it is unwise to invest in a portfolio which is not efficient.

²⁹A “no such thing as a free lunch” type of rule.

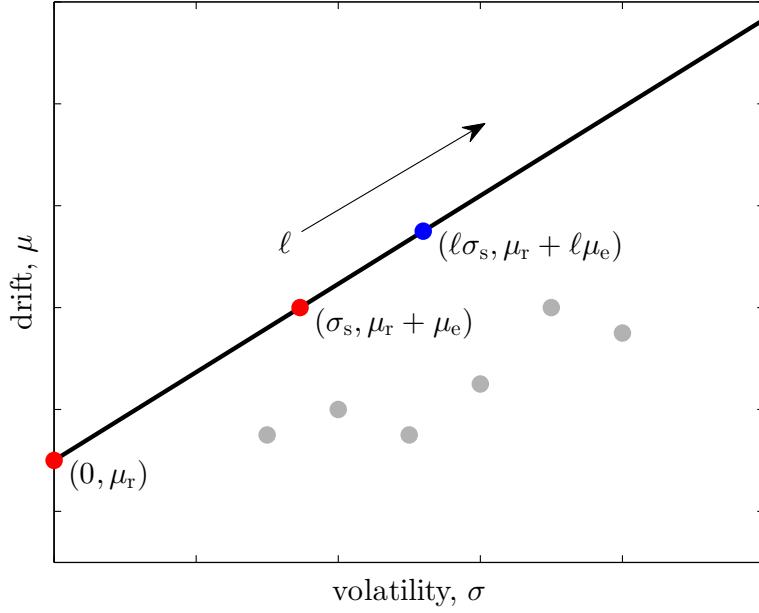


Figure 26: The Markowitz portfolio selection picture. The red dots are the locations in the (σ, μ) -plane of portfolios containing only the riskless (left) or risky (right) asset. The blue dot is one possible leveraged portfolio, in this case with $\ell > 1$. All possible leveraged portfolios lie on the black line, (Eq. 307). The grey dots are hypothetical alternative portfolios, containing different assets excluded from our simple portfolio problem. Their location below and to the right of the black line makes them inefficient under the Markowitz scheme.

In our problem, we are comparing portfolios with parameters $(\ell\sigma_s, \mu_r + \ell\mu_e)$. These lie on a straight line in the (σ, μ) -plane,³⁰

$$\mu = \mu_r + \left(\frac{\mu_e}{\sigma_s} \right) \sigma, \quad (307)$$

shown schematically in Fig. 26. Under Markowitz's classification, all of the leveraged portfolios on this line are efficient.³¹ Therefore, any leverage we choose gives a portfolio the classification would recommend. This does not help answer our question. By itself, Markowitz's approach is agnostic to leverage: it requires additional information to select a specific portfolio as the optimum. Markowitz was aware of this limitation and argued that the optimal portfolio could be identified by considering the investor's risk preferences [?]: “The proper choice among portfolios depends on the willingness and ability of the investor to assume risk.” The ultimate reliance on personal preferences is a theme that runs through all of economic theory, and we have seen examples of it in previous chapters. Of course, economic theory, or finance theory, is not meant to replace human judgement and imagination, nor is it supposed to force certain products and behaviours on people – but it is supposed to guide decisions. A statement like “this is the action that will eventually make your wealth grow fastest, assuming we have chosen models and estimated parameters correctly” is helpful and leaves plenty of room for judgement calls. As in decision theory in general,

³⁰Derived by eliminating ℓ from the equations $\mu = \mu_r + \ell\mu_e$ and $\sigma = \ell\sigma_s$.

³¹Indeed, in finance this line is called the efficient frontier.

risk preference are typically included in the portfolio selection problem through a utility function, and thereby the theory of finance inherits a major cornerstone of economics, along with all its problems.

5.1.4 Sharpe ratio

The Sharpe ratio [?] for an asset with drift μ and volatility σ is defined as

$$S \equiv \frac{\mu - \mu_r}{\sigma} \quad (308)$$

It is the gradient of the straight line in the (σ, μ) -plane which passes through the riskless asset and the asset in question. S is often used as a convenient shorthand for applying Markowitz's ideas, since choosing the portfolio with the highest S from the set of available portfolios is equivalent to choosing an efficient portfolio. The optimal leverage problem, however, important as it is, cannot be resolved by this procedure. The reason is this: all of our leveraged portfolios lie on the same line, (Eq. 307), and so all of them have the same Sharpe ratio, which is simply the line's gradient:

$$S_\ell = \frac{\mu_e}{\sigma_s}. \quad (309)$$

This is insensitive to the leverage ℓ , resulting in the same non-advice as the Markowitz approach. Sharpe also suggested considering risk preferences to resolve the optimal portfolio: "The investor's task is to select from among the efficient portfolios the one that he considers most desirable, based on his particular feelings regarding risk and expected return" [?]. Once more we encounter the theme of reliance on personal preferences in finance and economics. It is no surprise that this switch from formal recommendation (a portfolio should be on the efficient frontier/have a high Sharpe ratio) to personal preference (pick the one whose risks you feel most comfortable with) happens too soon, from our perspective. In general, we use a formal model as long as it's useful, and when we have pushed it to the point where it yields no further reliable answers we switch to personal judgement. The conceptual superiority of our analysis (relying on averages over time not over parallel worlds) allows us to push the model a little further, and the point where we previously had to switch now seems premature.

5.1.5 Expected return

We noted previously that the growth rate of the expectation value of the risky price is the risky drift, μ_s , also known as the expected return. This is because

$$\langle x_1(t_0 + \Delta t) \rangle = \langle x_1(t_0) \rangle \exp(\mu_s \Delta t), \quad (310)$$

which, as a multiplicative process, has growth rate

$$g_m(\langle x_1 \rangle) = \frac{\Delta \ln \langle x_1 \rangle}{\Delta t} = \mu_s. \quad (311)$$

It follows immediately from comparison of (Eq. 301) and (Eq. 305) that the expected value of the leveraged portfolio grows at

$$g_m(\langle x_\ell \rangle) = \mu_r + \ell \mu_e. \quad (312)$$

This illustrates why a portfolio theory which is insensitive to leverage, such as that of Markowitz and Sharpe³², is potentially dangerous. Because it doesn't alert the investor to the dangers of over-leveraging and considers any leverage optimal, the investor must find an additional criterion. There is nothing in the formalism that would prevent the investor to select as that additional criterion the expected return in (Eq. 312). Consequently he would maximise his leverage, $\ell \rightarrow \infty$. This, as we will shortly see, would almost surely ruin him.

5.1.6 Growth rate maximisation

We now understand the classical approach, as applied to a very simple portfolio problem, and we are aware of its limitations. What does our own decision theory have to say?

The time-average growth rate of the leveraged portfolio is

$$\bar{g}_m(\ell) \equiv \lim_{\Delta t \rightarrow \infty} \{g_m(x_\ell, \Delta t)\} = \lim_{\Delta t \rightarrow \infty} \left\{ \frac{\Delta \ln x_\ell}{\Delta t} \right\}. \quad (313)$$

Note that (Eq. 298) fully defines the dynamics – finance works with stochastic processes that include the mode of repetition. In contrast, classical decision theory works with gambles where the appropriate mode of repetition has to be guessed. This is a key advantage of finance over economics, and it means that while from the utility perspective the problem of portfolio selection is under-specified (we need to guess the utility function), from the perspective of time optimization it is not. We have all the information we need, the problem is well posed. The time-average growth rate will depend on ℓ . Inserting the expression for x_ℓ from (Eq. 306) in (Eq. 313) gives

$$\bar{g}_m(\ell) = \lim_{\Delta t \rightarrow \infty} \left\{ \frac{1}{\Delta t} \left[\left(\mu_r + \ell \mu_e - \frac{\ell^2 \sigma_s^2}{2} \right) \Delta t + \ell \sigma_s W(\Delta t) \right] \right\}, \quad (314)$$

which, since $W(\Delta t)/\Delta t \sim \Delta t^{-1/2} \rightarrow 0$ as $\Delta t \rightarrow \infty$, converges to

$$\boxed{\bar{g}_m(\ell) = \mu_r + \ell \mu_e - \frac{\ell^2 \sigma_s^2}{2}} \quad (315)$$

This is a quadratic in ℓ with an unambiguous maximum³³ at

$$\boxed{\ell_{\text{opt}} = \frac{\mu_e}{\sigma_s^2}} \quad (316)$$

ℓ_{opt} is the optimal leverage which defines the portfolio with the highest time-average growth rate. Classical theory is indifferent to where on the line in Fig. 26 we choose to be. Our decision theory, however, selects a particular point on that line,³⁴ which answers the question we posed at the start of Sec. 5.1.3. This is the key result. We note that all we need to know are the parameters μ_r , μ_s , and σ_s of the two assets in our market. In particular, it is defined objectively, with no

³²Both recipients of the 1990 Alfred Nobel Memorial Prize in Economic Sciences.

³³Derived, for example, by setting $\frac{d\bar{g}_m}{d\ell} = 0$.

³⁴Subsequently Markowitz became aware of this point, which he called the “Kelly-Latané” point in [?], referring to [?, ?].

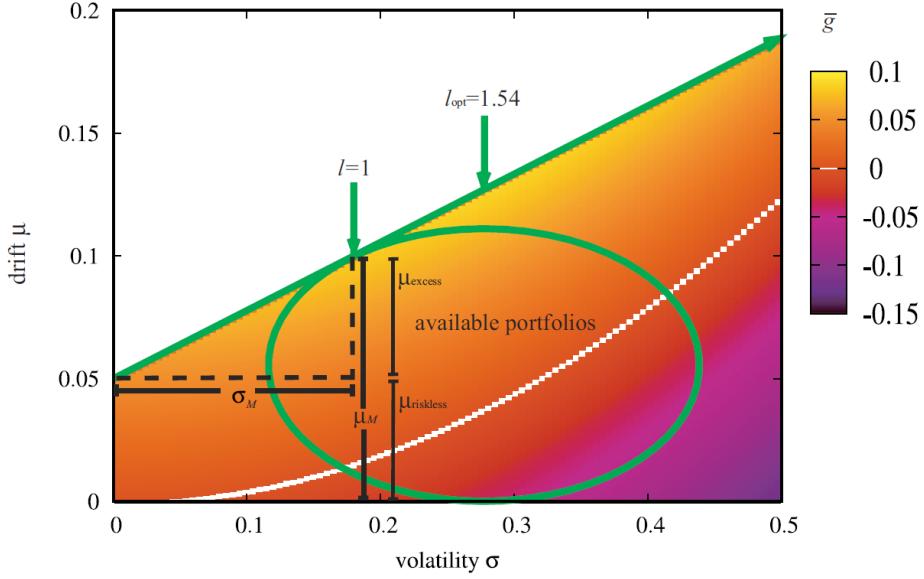


Figure 27: The augmented portfolio selection picture. The Markowitz picture is shown in green, with our model leveraged portfolios on the straight line (the efficient frontier) and hypothetical alternative portfolios within the ellipse (analogous to the grey dots in Fig. 26). This is overlaid on a colour plot of the time-average growth rate, \bar{g} . The optimal leverage, $l_{\text{opt}} \approx 1.54$, is marked at the location of the highest \bar{g} on the efficient frontier. Portfolios on the white curve have $\bar{g} = 0$. Eventually this will intersect the efficient frontier, at which point applying more leverage will produce a portfolio with negative long-run growth. Parameters are $\mu_r = \mu_e = 0.05$ per unit time and $\sigma_s = 0.18$ per square root time (denoted by μ_{riskless} , μ_{excess} , and σ_M in the figure). Adapted from [?].

reference to idiosyncrasies of the investor (except that we assume him to prefer fast growth to slow growth). Our approach can be useful when it is unknown who the “investor” is. Consider, for instance, a pension fund – it has to position itself in some way, manage its portfolio and the risks it is taking. The portfolio manager often cannot know who the investors are – there may be thousands of them. Optimizing the time-average growth rate would be a sensible goal that’s easily communicated, whereas trying to optimize the investment according to the investors’ risk preferences is simply impossible.

(Eq. 315) gives the time-average growth rate along the efficient frontier, where all of our leveraged portfolios lie. In fact, it’s easy to calculate the growth rate for any point in the (σ, μ) -plane: it is simply $\mu - \sigma^2/2$. Overlaying the Markowitz picture in Fig. 26 on the growth rate landscape is illuminating. In effect, it adds the information missing from the classical model, which was needed to distinguish between portfolios. This is shown in Fig. 27.

That (Eq. 315) defines an inverted parabola means that, even on the efficient frontier, there exist portfolios with $\bar{g}_m(\ell) < 0$. These occur for $\ell < \ell^-$ and $\ell > \ell^+$, where

$$\ell^\pm \equiv \ell_{\text{opt}} \pm \sqrt{\ell_{\text{opt}}^2 + \frac{2\mu_r}{\sigma_s^2}}. \quad (317)$$

This confirms our assertion at the end of Sec. 5.1.5, that an investor maximising

his leverage in either direction will, if he is able to apply enough leverage, lose wealth. Indeed, if his leveraging ability is unlimited, he will find to his horror what is easily seen in (Eq. 315), that $\bar{g}_m(\ell)$ diverges negatively as $\ell \rightarrow \pm\infty$. He will lose fast.

5.2 Stochastic market efficiency

5.2.1 A fundamental measure

Aside from being insensitive to leverage, the Sharpe ratio, $S = \mu_e/\sigma_s$, is a dimensionful quantity. Its unit is $(\text{time unit})^{-1/2}$. This means that its numerical value is arbitrary (since it depends on the choice of time unit) and tells us nothing fundamental about the system under study. For example, a portfolio with $S = 5$ per square root of one year has $S = 5(365)^{-1/2} \approx 0.26$ per square root of one day. Same portfolio, different numbers.

The optimal leverage, $\ell_{\text{opt}} = \mu_e/\sigma_s^2$, which differs from the Sharpe ratio by a factor of $1/\sigma_s$, is a dimensionless quantity. Therefore, its numerical value does not depend on choice of units and has the potential to carry fundamental information about the system.³⁵ We could view ℓ_{opt} as the fundamental measure of a portfolio's quality, similarly to how S is viewed in the classical picture. A portfolio with a high optimal leverage must represent a good investment opportunity to justify such a large commitment of the investor's funds.

However, the significance of ℓ_{opt} runs deeper than this. The portfolio to which ℓ_{opt} refers is that which optimally allocates money between the risky and riskless assets in our model market. Therefore, it tells us much about conditions in that market and, by extension, in the wider model economy. A high ℓ_{opt} indicates an economic environment in which investors are incentivised to take risks. Conversely, a low or negative ℓ_{opt} indicates little incentive to take risks. This raises a tantalising

Question:

Are there any special numerical values of ℓ_{opt} which describe different market regimes, or to which markets are attracted?

5.2.2 Relaxing the model

Our model market contains assets whose prices follow **GBM** with constant drift and volatility parameters.³⁶ Once specified, μ_r , μ_s , and σ_s are static and, therefore, so is ℓ_{opt} . This limits the extent to which we can explore the question, since we cannot consider changes in ℓ_{opt} . To make progress we need to relax the model. We must consider which parts of the model are relevant to the question, and which parts can be discarded without grave loss.

The **GBM**-based model is useful because it motivates the idea of an objectively optimal leverage which maximises the growth of an investment over time. It also provides an expression for ℓ_{opt} in terms of parameters which, in essence, describe the market conditions under which prices fluctuate. These parameters

³⁵See Barenblatt's modern classic on scaling [?].

³⁶A tautology, since (Eq. 298) only describes a **GBM** if μ and σ are constant in time.

have correspondences with quantities we can measure in real markets. All of this is useful.

However, we are ultimately interested in real markets, and their asset prices do not strictly follow **GBM** (because nothing in nature³⁷ truly does). In particular, real market conditions are not static. They change over time, albeit on a longer time scale than that of the price fluctuations. In this context, the model assumption of constant μ_r , μ_s , and σ_s is restrictive and unhelpful. We will relax it and imagine a less constrained model market where these parameters, and therefore ℓ_{opt} , are allowed to vary slowly. We will not build a detailed mathematical formulation of this, but instead use the idea to run some simple thought experiments.

5.2.3 Efficiency

One way of approaching a question like this is to invoke the concept of efficiency. In economics this has a specific meaning in the context of financial markets, which we will mention imminently. In general terms, an efficient system is one which is already well optimised and whose performance cannot be improved upon by simple actions. For example, a refrigerator is efficient if it maintains a cool internal environment while consuming little electrical power and emitting little noise³⁸. Similarly, Markowitz's portfolios were efficient because the investor could do no better than to choose one of them.

The “efficient market hypothesis” of classical economics treats markets as efficient processors of information. It claims that the price of an asset in an efficient market reflects all of the publicly available information about it. The corollary is that no market participant, without access to privileged information, can consistently beat the market simply by choosing the prices at which he buys and sells assets. We shall refer to this hypothesis as ordinary efficiency.³⁹

We will consider a different sort of efficiency, where we think not about the price at which assets are bought and sold in our model market, but instead about the leverage that is applied to them. Let's run a thought experiment.

Thought experiment: efficiency under leverage

Imagine that $\ell_{\text{opt}} > 1$ in our model market. This would mean that the simple strategy of borrowing money to buy stock will achieve faster long-run growth than buying stock only with our own money. If we associate putting all our money in stock, $\ell = 1$, with an investment in the market, then it would be a trivial matter for us to beat the market (by doing nothing more sophisticated than investing borrowed money).

³⁷We consider markets to be part of nature and appropriate objects of scientific study.

³⁸This is a subtle reference to a fridge whose presence once graced the offices of **LML**. It was not efficient.

³⁹This is not the most precise hypothesis ever hypothesised. What does it mean for a price to “reflect” information? Presumably this involves some comparison between the observed price of the asset and its true value contingent on that information. But only the former is observable, while the latter evades clear definition. Similarly, what does it mean to “beat the market”? Presumably something to do with achieving a higher growth rate than a general, naïve investment in the overall market. But what investment, exactly? We will leave these legitimate questions unanswered here, since our focus is a different form of market efficiency. The interested reader can consult the comprehensive review in [?].

Similarly, imagine that $\ell_{\text{opt}} < 1$. In this scenario, the market could again be beaten very easily by leaving some money in the bank (and, if $\ell_{\text{opt}} < 0$, by short selling).

It would strain language to consider our market efficient if consistent out-performance were so straightforward to achieve. This suggests a different, fluctuations-based notion of market efficiency, which we call stochastic market efficiency: it is impossible for a market participant without privileged information to beat a stochastically efficient market simply by choosing the *amount* he invests in stock, *i.e.* by choosing his leverage.⁴⁰ We believe real markets to be stochastically efficient. Therefore, we make the following

Hypothesis: stochastic market efficiency

Real markets self-organise such that

$$\ell_{\text{opt}} = 1 \quad (318)$$

is an attractive point for their stochastic properties.

These stochastic properties are represented by μ_r , μ_s , and σ_s in the relaxed model that permits dynamic adjustment of their values.

5.2.4 Stability

Another approach to the question in Sec. 5.2.1, whose style owes more to physics than economics, is to consider the stability of the system under study (here, the market) and how this depends on the value of the observable in question (here, ℓ_{opt}).

Systems which persist over long time scales tend to be stable. Many of the systems we find in nature therefore include stabilising elements. Unstable systems tend to last for shorter times,⁴¹ so we observe them less frequently. With this in mind, let's think about what different values of ℓ_{opt} imply for systemic stability.

Thought experiment: stability under leverage

Imagine that $\ell_{\text{opt}} > 1$ in our relaxed model. Since it is an objectively optimal leverage which does not depend on investor idiosyncrasies, this means that *everyone* in the market should want to borrow money to buy stock. But, if that's true, who's going to lend the money and who's going to sell the stock?

Similarly, imagine that $\ell_{\text{opt}} < 0$. This means that *everyone* should want to borrow stock and sell it for cash. But, if that's true, who's going to lend the stock and who's going to relinquish their cash to buy it?

⁴⁰This resembles ordinary efficiency except that we have replaced price by amount.

⁴¹We use the comparative “shorter” here. This does not mean short. It is quite possible for an unstable system to remain in flux for a long time in human terms, perhaps giving the illusion of stability. Indeed, much of classical economic theory is predicated on the idea that economies are at or close to equilibrium, *i.e.* stable. We would argue that economies are fundamentally far-from-equilibrium systems and must be modelled as such, even if their dynamics unfold over time scales much longer than our day-to-day affairs.

Unless there are enough market participants disinterested in their time-average growth rate to take the unfavourable sides of these deals – which in our model we will assume there aren’t – then neither of these situations is globally stable. It’s hard to imagine them persisting for long before trading activity causes one or more of the market parameters to change, returning ℓ_{opt} to a stable value.

This thought experiment suggests that we could observe markets with $0 \leq \ell_{\text{opt}} \leq 1$. We’ve defined things so that the optimal leverage is the proportion of one’s wealth ideally invested in the risk asset, *i.e.* in shares. $\ell_{\text{opt}} < 1$ probably doesn’t correspond to a macroeconomically desirable state, in the sense that people would be incentivised to keep their money in bank accounts rather than to invest it. But it wouldn’t be unstable purely from the leverage point of view. This hints at an interesting generalisation: what if both assets are risky? What if we’re comparing two share indexes or two shares, eliminating cash from our considerations? The same stability arguments would suggest that the optimal leverage in such a portfolio – now defined as the proportion ideally held in one of the assets – should be in the range $0 \leq \ell_{\text{opt}} \leq 1$, which reflects the symmetry between two risky assets. Our original hypothesis then describes the special case where one asset does not fluctuate.

Hypothesis: stochastic market efficiency for general asset pairs

On sufficiently long time scales, the range $0 \leq \ell_{\text{opt}} \leq 1$ is an attractor for the stochastic properties of pairs of risky assets.

Whether in our original setup real markets spend significant time in a phase with $\ell_{\text{opt}} < 1$ is difficult to tell. Realistic optimal leverage depends significantly on such things as trading costs, access to credit and risky assets in lending programs, infrastructure and technology. All of these factors differ among market participants. They suggest that measuring optimal leverage in the simplest way – using market prices only and assuming zero trading costs – will produce an over-estimate, compared to the value experienced by real market participants who incur realistic costs.

The dynamical adjustment, or self-organisation, of the market parameters takes place through the trading activity of market participants. In particular, this creates feedback loops, which cause prices and fluctuation amplitudes to change, returning ℓ_{opt} to a stable value whenever it strays. To be truly convincing, we should propose plausible trading mechanisms through which these feedback loops arise. We do this in [?]. Since they involve details about how trading takes place in financial markets (in which we assume the typical attendee of these lectures is disinterested) we shall not rehearse them here. The primary drivers of our hypothesis are the efficiency and stability arguments we’ve just made.

Furthermore, there are additional reasons why we would favour the strong form of the hypothesis over long time scales. The main one is that an economy in which ℓ_{opt} is close to, or even less than, zero gives people no incentive to invest in productive business activity. Such an economy would appear paralysed, resembling perhaps those periods in history to which economists refer as depressions. We’d like to think that economies are not systematically attracted

to such states. The other reasons are more technical, to do with the different interest rates accrued on deposits and loans, and the costs associated with buying and selling assets. These are described in [?].

5.2.5 Prediction accuracy

When we simply use observed price changes to compute changes in portfolio value, we will overestimate optimal leverage. Denoting an estimate from real data of ℓ_{opt} by ℓ^{est} , we will have $\ell^{\text{est}} > \ell_{\text{opt}}$. This is because real investments incur transaction costs and other costs associated with leveraging. We therefore expect naïvely measured values to be a little too big, $\ell^{\text{est}} > 1$.

Ignoring these effects for the moment, we can predict how close we expect observed optimal leverage to be to its predicted value, 1, when we estimate it from a finite time series, let's say of daily returns. Even assuming ideal conditions – that ℓ_{opt} really is attracted to 1 and that any effects that lead to systematic mis-estimation can be neglected, we expect random deviations from $\ell^{\text{est}} = 1$ to increase as the time series gets shorter. To take an extreme example, with daily data, the observed optimal leverage over a window of one day does not exist. Either $\ell^{\text{est}} \rightarrow +\infty$ if the risky return beats the deposit rate on that day; or $\ell^{\text{est}} \rightarrow -\infty$ if deposits beat the risky asset. Indeed, the magnitude of the observed optimal leverage will diverge for any window over which the daily risky returns are either all greater than, or all less than, the daily returns on federal funds. This is unlikely for windows of months or years but using daily data it happens commonly over windows of days or weeks. Even without this divergence, shorter windows are more likely to result in larger positive and negative optimal leverages because relative fluctuations are larger over shorter time scales.

To quantify this idea we compute $g_m(x_\ell, \Delta t)$, *i.e.* the time-average growth rate observed in an investment following (Eq. 305) after a finite time Δt . That's simply the expression on the RHS of (Eq. 314) without taking the $\Delta t \rightarrow \infty$ limit:

$$g_m(x_\ell, \Delta t) = \mu_r + \ell \mu_e - \frac{(\ell \sigma_s)^2}{2} + \frac{\ell \sigma_s W(\Delta t)}{\Delta t} \quad (319)$$

Maximizing this expression generates a noisy estimate for the optimal leverage over a window of length Δt :

$$\ell^{\text{est}}(\Delta t, N = 1) = \ell_{\text{opt}} + \frac{W(\Delta t)}{\sigma_s \Delta t}. \quad (320)$$

Thus, in the model, optimal leverage for finite time series is normally distributed with mean ℓ_{opt} and standard deviation

$$\text{stddev}(\ell^{\text{est}}(\Delta t)) = \frac{1}{\sigma_s \Delta t^{1/2}}. \quad (321)$$

We will use this quantity as the standard error for the prediction $\ell^{\text{est}} \approx 1$.

5.3 Applications of stochastic market efficiency

Our solution of the portfolio selection problem, and the concept of stochastic market efficiency that follows from it are momentous developments in the theory

of financial markets. While in a sense the puzzle pieces necessary for these developments have been around for a while, it seems that they haven't so far been put together in quite the way we've presented them. This is evident from many puzzles and questions that exist in finance and economics but which have a straight-forward solution in the conceptual space we have developed in these notes. Before we look at data in Sec. 5.4 to understand how accurately this fundamental theoretical work reflects empirical reality, we apply it to some of these famous puzzles to illustrate the type of solution the theory generates.

5.3.1 A theory of noise – Sisyphus discovers prices

According to stochastic market efficiency, prices of risky assets must fluctuate if an excess drift exists, $\mu_e > 0$, simply because the market would otherwise become unstable. But, if price fluctuations are necessary for stability, then the intellectual basis for price efficiency – that changes in price are driven by the arrival of new economic information – cannot be the whole truth. Or –depending on what is meant by “information” – it may be an empty circular statement. At least some component of observed fluctuations must be driven by the leverage feedbacks described in section Sec. 5.2, which enforce leverage efficiency and which have little to do with the arrival of meaningful economic information.

Black differentiated between information-based and other types of price fluctuation, referring to the latter as “noise” and regarding it as a symptom of inaccurate information and market *in*-efficiency [?]. However, substituting $\ell_{\text{opt}} = 1$ in (Eq. 316) yields

$$(\sigma_s)^2 = \mu_e. \quad (322)$$

Purely based on stochastic market efficiency, prices must fluctuate, and we can even quantify by how much. An asset whose expectation value grows faster than the value of the riskless asset must fluctuate; otherwise systemic stability will be undermined. This is a radical departure from conventional thinking, and it has practical consequences. For instance, prices “discovered” at ever higher trading frequencies must necessarily reveal more ups and downs, but this noise is self-generated, imposed by the requirement of leverage stability. That stability is the genesis of volatility constitutes a theory of noise requiring no appeal to the arrival of unspecified information, accurate or not.

5.3.2 Solution of the equity premium puzzle

The term “equity premium” has been used to describe the “premium” I receive for holding “equity” – meaning the extra growth rate my wealth experiences, compared to riskless interest rates, if I invest it in shares, or some other risky asset. We denote this with the symbol π^m (for premium).

Puzzles usually arise because we look at things from the wrong angle, with a mental model that doesn't reflect reality. The equity premium puzzle is no exception. The researchers who first studied the equity premium had a model in mind whereby equity prices are set based on the consumption preferences of the population [?]. We won't go into these models in detail because they're the wrong angle. But the story is this: consumption-based asset pricing models come to the conclusion that no one should ever hold cash. In these models only people who are pathologically terrified of losing money would hold cash, and such people just don't exist. But if you assume that they don't exist, then

the models would predict a very different equity premium. So something is not working. In 2016 LeRoy summarized the state of the debate as follows [?]: “Most analysts believe that no single convincing explanation has been provided for the volatility of equity prices. The conclusion that appears to follow from the equity premium and price volatility puzzles is that, for whatever reason, prices of financial assets do not behave as the theory of consumption-based asset pricing predicts.”

Of course the difference between the time-average growth rates of the risky asset ($\ell = 1$) and the riskless asset ($\ell = 0$) can be measured. It is

$$\pi^m \equiv \bar{g}_m(1) - \bar{g}_m(0) \quad (323)$$

$$= \mu_e - \frac{(\sigma_s)^2}{2}. \quad (324)$$

What value would we expect the equity premium to take in a real market? Substituting (Eq. 322) into (Eq. 324), it follows that the equity premium is attracted to

$$\pi^m = \frac{(\sigma_s)^2}{2}. \quad (325)$$

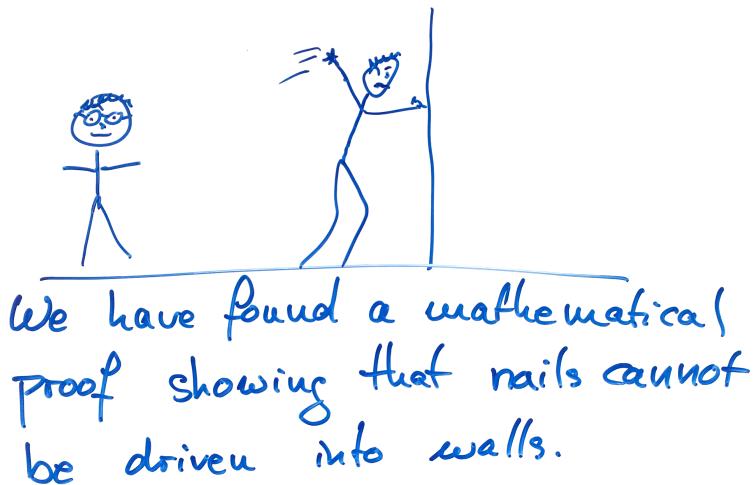
It is important to remember that any theoretical prediction comes with a band of uncertainty around it. The next step is, therefore, to estimate the uncertainty in the equity premium. We do this by considering finite measurement times and substitute (Eq. 319) into (Eq. 323)

$$\text{stdev}(\pi^m(\Delta t)) = \frac{\sigma_s}{\Delta t^{1/2}}. \quad (326)$$

In Sec. 5.4 we will use this as our definition of one statistical standard error. The tension may by now have become unbearable, so here’s a sneak preview of what’s to come empirically: Our estimate of $(\sigma_s)^2$ for the **Deutscher Aktienindex (German stock index) (DAX)** since its inception in 1987 is 5.3% p.a.. Half of that is 2.6% p.a., and the standard error is 4.2% p.a., meaning the 2-standard-error range around the predicted value of 2.6% p.a. is $-5.8\% \leq \pi^m \leq 11.0\%$ p.a.. We will later see that this range is systematically biased: it underestimates the real equity premium. For now we note that in a review of 150 textbooks discussing the equity premium, Fernández finds estimates for π^m in a range from 3% p.a. to 10% p.a., broadly consistent with our predictions [?]. We hasten to add that the 150 textbooks are not consistent in their definitions of the equity premium, so these numbers can only be a rough guide. The simplicity of our input is important: stability and the standard **GBM** model for price dynamics.

The equity premium puzzle is an interesting case study of economic science in operation. The literature on the puzzle is large and often takes a psychological and individual-specific perspective. For instance, a more risk-averse individual will demand a higher equity premium. Models of human behaviour enter both into the definition of the equity premium – which lacks consensus [?] – and into its analysis. The problem is treated in wordy essays, and it’s also treated using impenetrably complicated formal models. But this additional complexity (compared to our treatment) doesn’t add much. It seems to be a result of science incrementally going in one direction and failing to retrace its steps and try a different angle.

The framework we have developed here takes a psychologically naïve perspective, without reference to human behaviour or consumption. It is analytically



Hammer? No no. The field of nailing is defined by the exclusive use of bare hands.

Figure 28: The equity premium puzzle.

embarrassingly simple. Only our one key insight was needed: performance over time is not performance of the ensemble. We regard the correct prediction of the equity premium by stochastic market efficiency as the long-sought resolution of the equity premium and price volatility puzzles. It is worth noting that the experts disagree with us: the equity premium puzzle, in their minds, is the fact that observed equity premia cannot be explained with consumption-based asset pricing models. In our view that simply means it's time to throw out consumption-based asset pricing models, whereas clinging on to them can be summarized in the cartoon in Fig. 28.

5.3.3 Central-bank interest rates

Our observations are also relevant to the issue of setting a central bank's lending rate. The rate setter would view the total drift μ_s of an appropriate asset or index as given, and the risk-free drift μ_r as the central bank's rate. If the aim is to achieve full investment in productive activity without fuelling an asset bubble, then this rate should be set so that $\ell_{\text{opt}} = 1$. Since $\ell_{\text{opt}} = \mu_s / (\sigma_s)^2$ and $\mu_e = \mu_r - \mu_s$, this is achieved by setting

$$\mu_r = \mu_s - (\sigma_s)^2. \quad (327)$$

Using values for μ_s and σ_s estimated in section Sec. 5.4, the optimal interest rate between 1988 and 2018 for the US comes out as 9% *p.a.*, suggesting that actual interest rates over the analysed period have been in a region where they can inflate leverage bubbles (the geometric average on 10-year maturity Treasury bills was about 4.7% *p.a.* lower than this value). The effect is mitigated by trading costs, meaning that 9% is an overestimate of the optimal interest rate, nonetheless it is hard to deny that asset bubbles were inflated over this period. The task of the central banker can be seen as the task of estimating μ_r and

σ_s in the relevant way. This will involve choices about data and timescales which are far from trivial. For instance, in our data analyses at any given time there is an estimate for μ_s and one for σ_s for each possible length of lookback window. Operational matters aside, stability with respect to leverage is an important consideration for any central bank. Leverage efficiency provides a simple quantitative basis for a rate setting protocol and may frame qualitative discussions about interest rates in a useful way.

5.3.4 Fraud detection

We will see in the next section that stochastic market efficiency is real. Prices of real traded assets more or less obey the constraints dictated by systemic stability. Of course, over short time scales fluctuations will be large, there are all manner of difficult-to-model effects in real trading environments. These include transaction costs and other operational costs. Still – a realistic asset should more or less satisfy stochastic market efficiency.

But what if it doesn't? What if there is an asset that consistently, and at low volatility outperforms bank deposits? First of all, we now know that such behavior is a challenge to systemic stability. Because of this, we don't expect it to survive for long. Where it does survive for long, one possible explanation is fraud. A common type of fraud is the so-called Ponzi scheme: the fraudster invents an attractive-looking past performance of a portfolio or asset value and entices new investors to give him their money. Instead of investing the money in the non-existent asset, it is passed on to pay off earlier investors and the fraudster siphons off a handy profit. Since the performance of the asset price is invented, there is no strong reason for it to obey stochastic market efficiency. Below we will test the Bernie-Madoff ponzi scheme and ask: was it too good to be true from the perspective of stochastic market efficiency? We will ask the same question about bitcoin: is it too good to be true from this perspective?

5.4 Real markets – stochastic market efficiency in action

In Sec. 5.3 we went through some earth-shattering consequences of leverage efficiency. Of course we wouldn't have done that if there wasn't strong evidence of this organizing principle actually working in practice. Let's get some data and try it out.

We test the stochastic efficiency hypothesis in real markets, quite naively, by backtesting leveraged investments. The simplest thing to check is this: take two time series, one of the returns of a very stable, low-volatility, asset, like bank deposits, and the other of the returns of a more volatile asset, like shares. Then try out all possible fixed-leverage investment strategies and see which one does best. The leverage where that happens is a real-world estimate of ℓ_{opt} , which we'll call ℓ_{est} .

Of course we can argue about the data until the cows come home – which precise data set should be used, what biases will it introduce, and so on. But let's set those worries aside for the moment and just try something.

5.4.1 Backtests of constant-leverage investments

An investment of constant leverage is backtested using two time series, $r_s(t)$ (risky returns) and $r_r(t)$ (returns on bank deposits) as illustrated in Fig. 25.

1. We start with equity of $x_\ell(t_0; \ell) = \$1$, consisting of $\$ \ell$ in the risky asset and $\$(1 - \ell)$ in bank deposits.
2. Each day the values of these holdings are updated according to the historical returns, so that

$$\ell x_\ell(t; \ell) \rightarrow r_s(t) \ell x_\ell(t; \ell) \quad (328)$$

$$(1 - \ell) x_\ell(t; \ell) \rightarrow r_r(t) (1 - \ell) x_\ell(t; \ell). \quad (329)$$

3. The portfolio is then rebalanced, *i.e.* some risky holdings are “bought” or “sold” (swapped for cash) so that the ratio between risky holdings and equity remains ℓ .

In step 1, we could include extra fees for borrowing cash or stock, and in step 2 we could include transaction costs. For the sake of simplicity we leave out these effects and refer the reader to [?]. The result of such extra complexity is two-fold: portfolios with leverage $\ell < 0$ or $\ell > 1$ are penalized by borrowing costs, and any portfolios except those with $\ell = 0$ or $\ell = 1$ are penalized by trading costs. Both effects reinforce stochastic market efficiency, in the sense that they bring $\ell_{\text{opt}} \rightarrow 1$.

But in the simplest instance, steps 1–3 result in the following protocol, which is a discretized version of (Eq. 305)

$$x_\ell(t) = \underbrace{r_s(t) \ell x_\ell(t - \Delta t)}_{\text{new risky holdings}} + \underbrace{r_r(t) (1 - \ell) x_\ell(t - \Delta t)}_{\text{new bank deposits}}, \quad (330)$$

which we repeat until the final day of the backtest, t_{\max} , when the final equity $x_\ell(t_{\max})$ is recorded. Figure 29 shows a few trajectories of leveraged investments in the S&P500 total return index (S&P500TR) at different leverages ℓ .

The optimal leverage is that which maximizes the final equity – the trajectories $x_\ell(t)$ are turned into curves $x_\ell(t_{\max})$ by fixing $t = t_{\max}$, see Fig. 29. If at any time the equity falls below zero, the investment is declared bankrupt and the backtest is considered invalid for the corresponding leverage. This happens when the leverage is very high and the risky asset drops in value, or when it’s very negative and the risky asset rises in value. Between these extremes, a smooth curve emerges, resembling a Gaussian bell-shape (or an upside-down parabola on logarithmic vertical scales).

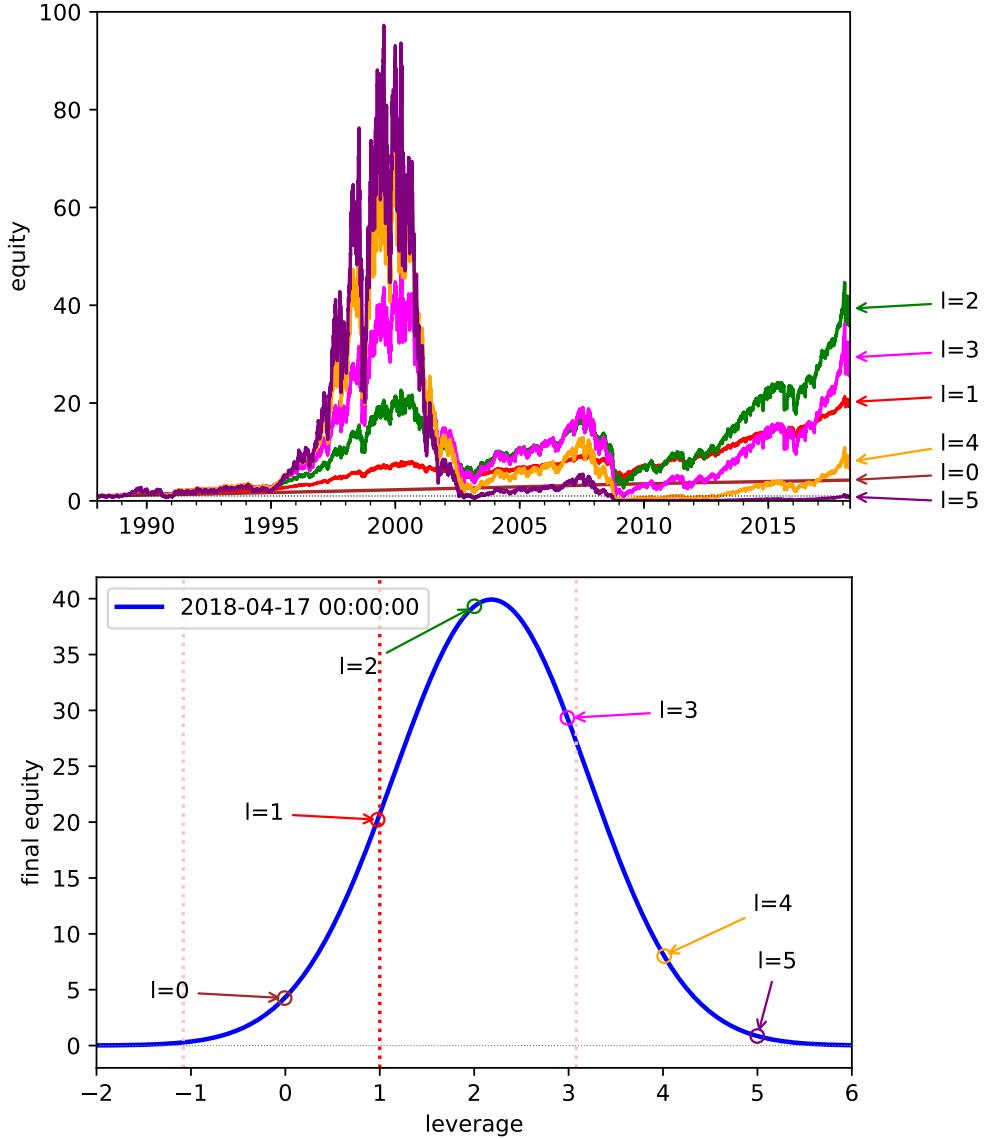


Figure 29: **Top:** equity $x_\ell(t)$ as it evolves over time, in investments of initially \$1 in the S&P500TR at different constant leverages, rebalanced daily as in Fig. 25. For riskless returns we use interest rates of 10-year T-bills. Initially, as leverage increases $\ell = 0 \rightarrow 1 \rightarrow 2$ the benefits of investing in the S&P500TR manifest themselves. But eventually, as $\ell = 3 \rightarrow 4 \rightarrow 5$, harmful fluctuations become so large that returns diminish. Each leverage produces one value for the final equity. **Bottom:** Final equity, $x_\ell(t_{\max})$, for 500 different leverages (where t_{\max} is 1 March 2018 in this case). Each leverage produces a ragged time series of equity (top panel). But the final equity as a function of leverage is a smooth curve. The vertical dotted lines indicate our prediction of the position of the optimum at $\ell = 1$, and the range up to 2 standard errors away.

5.4.2 Data sets

We want to compare the true performance of one asset to that of another, and therefore it's important to find time series that really resemble changes in equity over time that an investment would have experienced. A stock market index would be nice because it will give a broad overall impression. It won't depend too much on the specific fortunes of any given company.

Strangely, most stock indexes are simply weighted averages of (free-float) market capitalization of a bunch of listed companies, but when one of those companies pays a dividend of \$10, say, and its shares correspondingly drop by \$10, the index drops too. We don't want that, so we'll have to find an index that properly accounts for dividends.

S&P500TR The [S&P500TR](#) includes dividends as desired, so we'll use it as the risky asset and play it against 10-year T-bills as the riskfree asset.

DAX Another index that includes dividends is the German [DAX](#), and we'll try that out too. In this case we will use German overnight deposits for the riskfree asset.

Bitcoin As any scientific model, stochastic market efficiency applies within some range of conditions. We will use Bitcoin to discover the limits of this range. We developed our hypothesis using our knowledge and intuition of economies, stock markets, and central banks. Let's take it outside of this context and see what happens if we use Bitcoin as the risky asset. It doesn't pay any dividends, so we don't have to worry about that, but its performance has been very different from that of a stock market, so it will be informative to see what will happen to our hypothesis.

Madoff We take the idea of finding the limits of the range of applicability one step further, by using an asset that has officially been declared bullshit: investments in Bernie Madoff's Ponzi scheme. Monthly returns were included in a now famous complaint filed to the [Securities and Exchange Commission \(SEC\)](#) by Harry Markopolos in 2005 [?]. The complaint was ignored by the [SEC](#), and Madoff happily continued his scheme until the turbulent financial events of 2008 brought to light what he'd been up to. We digitized the returns in Markopolos's complaint and ran the same backtests for Madoff as for the other assets.

For all assets, we will overestimate real optimal leverage in the most straightforward backtest. Here are some reasons:

1. Whenever trading occurs to rebalance the portfolio, trading costs would be incurred in reality.
2. Money borrowed for leveraging up (and shares borrowed for shorting) come at a premium that the investor has to pay.
3. Stock indexes reflect well diversified portfolios of successful companies – they are affected by survivorship bias because unsuccessful companies leave the index.

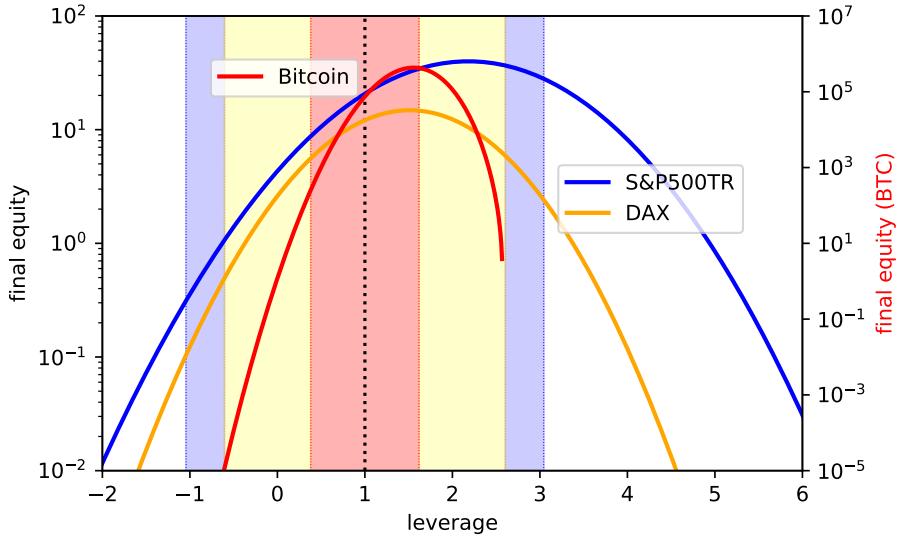


Figure 30: Final equity $x_\ell(t_0; \ell)$ for investments of initially \$1 in the S&P500TR (blue), the DAX (yellow), and Bitcoin (red, scale on the right). The maxima of all three curves are near the predicted optimum of $\ell_{\text{opt}} = 1$, where by “near” we mean that they are all within 2 standard errors of the prediction, without any correction for the biases introduced by neglecting trading costs.

We could try to correct for this bias, and we have done that in [?]. The necessary assumptions make the results more realistic but also more dependent on subjective guesses, so we’ll just stick to the simplest case here and note that it will produce an over-estimate of ℓ_{opt} .

5.4.3 Full time series

The bottom panel of Fig. 29 shows the leverage-return curve for the S&P500TR. The optimal leverage is a little greater than 1, but still within 2 standard errors from the prediction. Without further ado, let’s add to this figure the same curves for the DAX and Bitcoin, this time on logarithmic vertical scales to see a bit more structure, Fig. 30.

The overall impression that emerges is this: leverage efficiency is reasonably satisfied for these assets. The shaded areas in Fig. 30 show the predicted ranges, 2 statistical standard errors to the left and right from $\ell_{\text{opt}} = 1$, and all observed maxima of the curves are within these bands. We also see a convincing bias: all estimates are greater than 1, as expected given the bias in the estimate that we mentioned earlier.

From a scientific point of view it’s not very interesting to show lots of cases where a theory gives good predictions. We want to know the limits of the theory. When does it not apply? Where does it break down? Before we looked at the data we thought that Bitcoin might be an example of an asset that doesn’t obey stochastic market efficiency. But it looks just as predicted – unspectacular. We didn’t have a specific reason to suspect that the theory wouldn’t apply to Bitcoin, it just seemed like an extreme asset, unlike the assets we had in mind when we developed the theory.

But let's see what happens where the theory really doesn't apply. In Fig. 31 we add to the curves of Fig. 30 the return-vs.-leverage curve for Bernie Madoff's fund. This is instructive because it shows just how different the results could have been. If it weren't for leverage efficiency optimal leverage for the **S&P500TR**, for example, could be miles away from our prediction. We have to show the Madoff data in a separate figure because the scales are so different that the differences between Bitcoin, **S&P500TR**, and the **DAX** become barely visible, and we thought they may be of interest. Apart from showing the limits of the range of applicability of our theory, the Madoff data suggest that leverage-return curves can help detect investments that are too good to be true, *i.e.* fraud.

Of course, Madoff could have chosen the invented returns of his fund in a way that's consistent with stochastic market efficiency, just to have something credible to show to prospective victims of his fraud. But apparently he didn't bother to do that, and people believed that he'd really found a way to print money. As a former CEO of Nasdaq he himself had sufficient credibility, never mind the data.

That stochastic market efficiency really doesn't apply to Madoff's returns is a good sign – showing that a theory fails to predict things it shouldn't be able to predict is important. A theory about asset price fluctuations that applies even to fictitious prices like Madoff's would be suspicious – it would probably not say much about prices at all but just be a statement that's generally true for a much broader class of phenomena. Having said this, introducing realistic transaction costs, leveraging something by a factor of 100 or 200 is extremely expensive, and the Madoff optimal leverage comes down significantly in a more realistic setup. Nonetheless, in Fig. 31 Madoff's returns have a statistical signature that is unequivocally different from prices arising through trading that we have investigated.

5.4.4 Shorter time scales

In Sec. 5.2.5 we derived an expression, (Eq. 321), for the variance of optimal leverage that we expect to observe in a finite time series, and we used this to arrive at a statistical error estimate, a scale on which to judge whether leverage efficiency holds or not. But we can use (Eq. 321) as a prediction in itself: is the sample variance of ℓ_{opt} , measured in many windows of size Δt well described by (Eq. 321)? We can't make the time series longer than they are, but we can make the shorter. In Fig. 32 we collect statistics of $\ell_{\text{opt}}^{\text{est}}$ estimated in non-overlapping time windows and find good agreement with the model-specific prediction.

The structure we have identified – leverage efficiency – operates on all time scales from weeks to decades. This broad range of applicability supports our theory of noise in Sec. 5.3.1: it is a requirement of stability that asset prices fluctuate, and the shorter the time scales the less significant any economic information becomes. Thinking of price changes as a reflection of new information may be relevant on time scales of years or decades, where the real economic fortunes of companies become apparent. On time scales of days or minutes, let alone milliseconds, price movements usually have nothing to do with economic information.

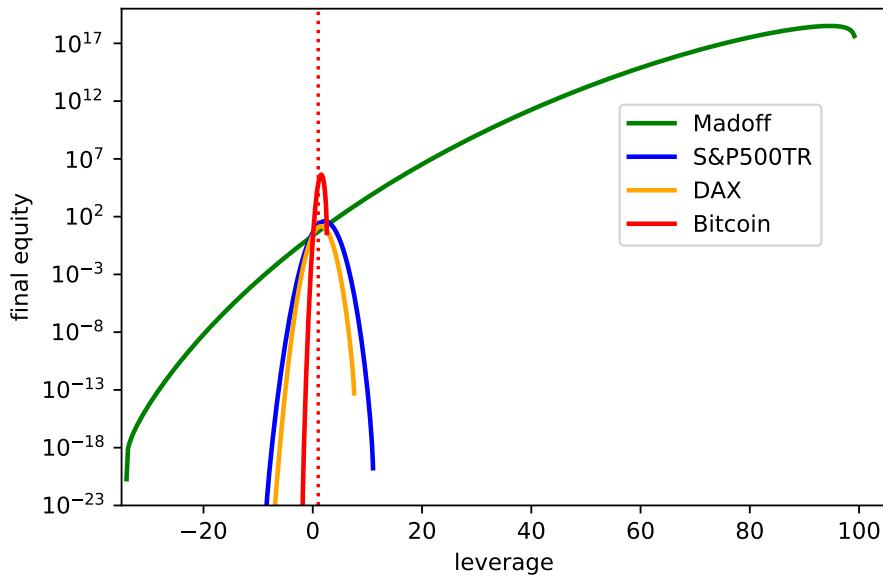


Figure 31: Final equity for investments of initially \$1 in the S&P500TR (blue), the DAX (yellow), Bitcoin (red), and Bernie Madoff's ponzi scheme. The maxima for the real assets cluster near the predicted value $\ell_{\text{opt}} = 1$. Madoff's freely invented performance had such low volatility that a leverage of 100 would have been optimal, even if rebalancing could have only occurred once per month. At higher rebalancing frequencies (had the asset actually existed) the green curve would be seen to be the left end of a parabola whose maximum may well be at 200 or 300.

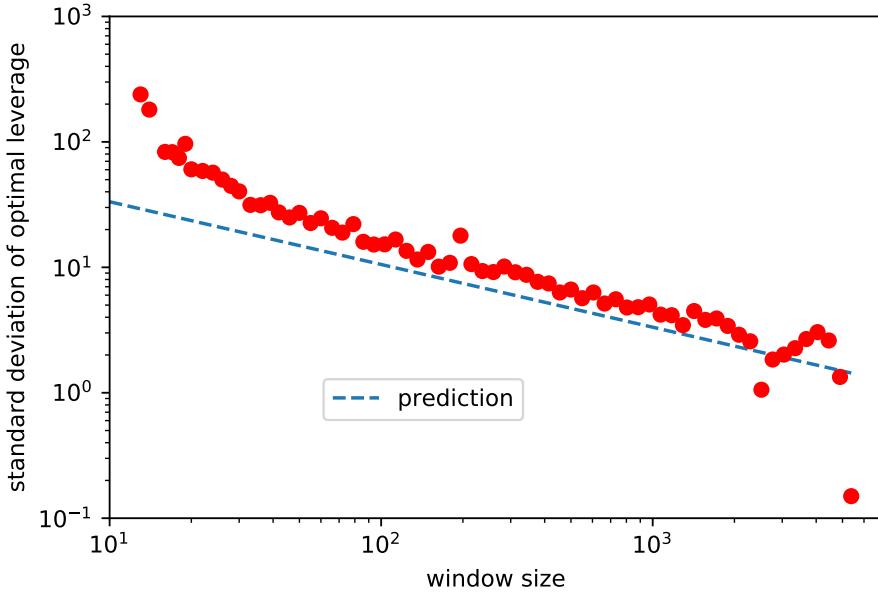


Figure 32: The red dots show the standard deviation of samples of $\ell_{\text{opt}}^{\text{est}}(\Delta t)$ as a function of window length measured in days. The blue dashed line shows the prediction of (Eq. 321) using the estimate of σ_s obtained by fitting a parabola to the S&P500TR curve in Fig. 30.

5.5 Discussion

The primary aim of this final lecture was to demonstrate that the mathematical formalism we have developed to conceptualise randomness in economics, which started with a simple model of wealth evolution by repetition of a gamble, is very powerful. It does more than simply create a rigorous and plausible foundation for economic theory. In particular, because the framework is epistemologically sound, we can make testable predictions, which we can corroborate empirically using real economic data. We could not have guessed from our simple coin-tossing game that we would end up making a prediction about the fluctuations of stock markets or those of bitcoin. The simple but deep conceptual insight that the ergodicity question has been overlooked ultimately shed a good deal of light on the equity premium puzzle, informed the debate of how to set central-bank interest rates, and provided a new way of thinking about noise and the stabilizing role of price fluctuations. What other surprising predictions can we make in this formalism? That, dear reader, is a question for you.

Acronyms

BM Brownian Motion.

DAX Deutscher Aktienindex (German stock index).

GBM Geometric Brownian motion.

GDP Gross domestic product.

LHS Left-hand side.

LML London Mathematical Laboratory.

PDF Probability density function.

RGBM Relocalizing geometric Brownian motion.

RHS Right-hand side.

S&P500TR S&P500 total return index.

SDE Stochastic differential equation.

SEC Securities and Exchange Commission.

List of Symbols

a A scalar.

A An observable.

C Replacement cost of a ship.

d Differential operator in Leibnitz notation, infinitesimal.

δt A time interval corresponding to the duration of one round of a gamble or, mathematically, the period over which a single realisation of the constituent random variable of a discrete-time stochastic process is generated..

δ Most frequently used to express a difference, for instance δx is a difference between two wealths x . It can be the Kronecker delta function, a function of two arguments with properties $\delta(i, j) = 1$ if $i = j$ and $\delta(i, j) = 0$ otherwise. It can also be the Dirac delta function of one argument, $\int f(x)\delta(x - x_0)dx = f(x_0)$.

Δ Difference operator, for instance Δv is a difference of two values of v , for instance observed at two different times.

Δt A general time interval..

η Langevin noise with the properties $\langle \eta \rangle = 0$ and $\langle \eta(t_1)\eta(t_2) \rangle = \delta(t_1 - t_2)$.

f Generic function.

\mathcal{F} Force.

F Fee to be paid.

g Growth rate.

G Gain from one round trip of the ship.

g_{est} Growth rate estimator for finite time and finite ensemble size.

- $g_{\mathbf{a}}$ Additive growth rate, *i.e.* rate of change.
- $\overline{g}_{\mathbf{a}}$ Time-average additive growth rate, *i.e.* long-term rate of change.
- $g_{\langle \rangle}$ Exponential growth rate of the expectation value.
- $g_{\mathbf{m}}$ Multiplicative growth rate.
- \bar{g} Time-average exponential growth rate.
- $\overline{g}_{\mathbf{m}}$ time-average multiplicative growth rate.
- i Label for a particular realization of a random variable.
- j Label of a particular outcome.
- J Size of the jackpot.
- k dummy.
- K Number of possible values of a random variable.
- ℓ Leverage.
- L Insured loss.
- ℓ^- Smallest leverage for zero time-average growth rate.
- ℓ_{opt} Optimal leverage.
- $\ell_{\text{opt}}^{\text{est}}$ Estimate of optimal leverage from data.
- ℓ^+ Largest leverage for zero time-average growth rate.
- ℓ^\pm Leverages for zero time-average growth rate.
- \mathbf{m} Mass.
- m Index specifying a particular gamble.
- μ Drift term in BM.
- μ_r Drift of riskless asset.
- μ_s Drift of risky asset.
- μ_e Excess drift.
- n n_j is the number of times outcome j is observed in an ensemble.
- N Ensemble size, number of realizations.
- \mathcal{N} Normal distribution, $x \sim \mathcal{N}(\langle p \rangle, \text{var}(p))$ means that the variable p is normally distributed with mean $\langle p \rangle$ and variance $\text{var}(p)$.
- o Little-o notation.
- p Probability, p_i is the probability of observing event i in a realization of a random variable.

- \mathcal{P} Probability density function.
 φ Reallocation rate in [RGBM](#).
 π^m Equity premium in our model.
 q Possible values of Q . We denote by q_i the value Q takes in the i^{th} realization, and by q_j the j^{th} -smallest possible value.
 Q Random variable defining a gamble through additive wealth changes.
 r Random factor whereby wealth changes in one round of a gamble.
 r_r Factor whereby wealth deposited in a bank changes.
 r_s Factor whereby wealth invested in stock changes.
 $r_{\langle \rangle}$ Expectation value of growth factor r .
 \bar{r} Average growth factor over a long time.
 s Dummy variable in an integration.
 S Sharpe ratio.
 σ Magnitude of noise in a Brownian motion.
 σ_s Volatility of risky asset.
 t Time.
 T Number of sequential iterations of a gamble, so that $T\delta t$ is the total duration of a repeated gamble..
 t_0 Specific value of time t , usually the starting time of a gamble..
 t_{\max} Final time in a sequence of repeated gambles..
 τ Dummy variable indicating a specific round in a gamble.
 u Utility function.
 v Stationarity mapping function, so that $v(x)$ has stationary increments.
var Variance.
 W Wiener process, $W(t) = \int_0^t dW$ is continuous and $W(t) \sim \mathcal{N}(0, t)$.
 x Wealth.
 \bar{x} Time-average of x . With subscript Δt , this is a finite-time average, without the subscript it refers to the infinite-time average..
 \mathbf{x} Position.
 x_0 Value of an investment in the riskless asset.
 x_1 Value of an investment in the risky asset.
 ξ A standard normal variable, $\xi \sim \mathcal{N}(0, 1)$.

x_{ℓ} Value of an investment in a leveraged portfolio.

Y Random variable that is a function of another random variable, Z .

z Generic value of a random variable.

Z Generic random variable.