

Properties of Pricing Kernels

Revised: November 8, 2014

Our next step is to inject some quantitative content into asset pricing models with macroeconomic foundations — macro-finance, for short. In doing so, we retrace some of the key steps of the last thirty years. The term macro-finance means (a) we're interested in returns on aggregate assets like bonds and equity indexes and (b) we'd like to account for those returns with a macroeconomic model, such as one with a representative agent.

A short summary would go like this:

- Mehra and Prescott (JME, 1985) on the equity premium. They showed that a representative agent model with power utility can't account for the observed average excess return on equity with reasonable risk aversion. We get the sign right, but not the magnitude.
- Hansen and Jagannathan (JPE, 1991) traced the problem to the pricing kernel. The so-called HJ bound shows that the dispersion of the pricing kernel is bounded below by the Sharpe ratio of any traded asset, including equity. Therefore the issue with the equity premium has to do with the pricing kernel, not the dividends to which equity is a claim. I like a variant of this result, in which dispersion is measured by entropy, something we'll define when we get to it.

In short, when we observe high excess returns or Sharpe ratios, they tell us that there must be a lot of dispersion in the pricing kernel — dispersion being here a suitably vague term for variability that we'll define more precisely later on. Any model lacking such dispersion is dead from the start. With power utility, that typically means high risk aversion, which brings us back to what degree of risk aversion is reasonable. The evident problems with the representative agent power utility model is the key driving work in this area.

In all of this, we'll use a timing convention in which t is now and $t + 1$ is later. With time measured in years, $t + 1$ would be one year from now. That's similar to what we've done so far, but with t taking the place of date 0 and $t + 1$ taking the place of date 1. The change is superficial, but makes the comparison with data more natural.

1 The nature of research

Lots of people do research: analysts, academics, etc. The content varies, but there's a common theme. Research is about (i) asking an interesting question and (ii) providing an informative answer. The route from (i) to (ii) varies, because we never know what we'll find. That's why we call it research: we don't know the answer until we do it, and sometimes not even then.

So what makes a good question? Here are some examples to help us think about that:

- What will GDP growth be next year? That's not a great question. The only way to resolve it, really, is to wait and see what happens. Perhaps we could modify it: What is the best method for predicting next year's GDP growth? That's a well-defined statistical exercise that we could imagine making some progress on. Still not wildly interesting, at least to me, but it's a step forward.
 - What is the population of the US? Again, not a great question. We look up the answer and we're done. Although a closer look would tell us that we never really know the population. The Census attempts to come up with an answer every ten years, but it's well-known to be an approximation. Probably a pretty good one, but an approximation. On the other hand, thinking about the population could lead us to better questions. What fraction of the population is above 70? What fraction has a college education? What do the answers tell us about how the US economy works? You get the idea: even a bad question can get us thinking in a useful way.
 - What have the average returns been on bonds and equity over the last century? This is a little more complex, but still in essence a lookup. We need to collect data on returns and compute sample means. When we do that, we'll run across some questions about the definitions of the assets: what equity? what bonds? You can see an example of such an effort in Table 1. There we've expanded the question to include the standard deviation, skewness, and excess kurtosis.
 - Why is the excess return on equity roughly 4%? This one calls for a model. Can we construct a model that has this feature? Is it plausible? This is the question addressed by Mehra and Prescott, one we'll address ourselves in much the same way they did.
- More generally, why do some assets have higher returns, on average, than others? Should we invest more in them? Can we make money doing this for others? Each of these questions has both practical and intellectual interest.

What questions appeal to you? What would you like to know more about? Keep notes, perhaps with links, and come back to them now and then. You'll remind yourself how much fun it is to think about new things and, sometimes, to make progress in your understanding of them.

2 Properties of excess returns and consumption growth

We'll start with the evidence on asset returns, specifically US assets over the last 100+ years. We summarize the basic features of such returns in Table 1 and Figure 1. Table 1 includes some of the properties of real (inflation-adjusted) returns on equity (the S&P 500) and bonds (one-year Treasuries) for the period 1889-2009. It also includes similar properties of consumption growth, for reasons that will be clear shortly.

It's clear from Figure 1 that the variation in excess returns on equity is closely related to variation in aggregate consumption growth. In that sense, returns are a macroeconomic phenomenon: returns tend to be high when consumption growth is high.

Beyond this, we have some useful summary statistics. We compute them in levels of returns (r^1 and r^e) and logs ($\log r^1$ and $\log r^e$). The same with consumption growth: $g_{t+1} = c_{t+1}/c_t$

and $\log g_{t+1}$. You might be asking yourself: Why logs? The answer is that it fits nicely with some theory we'll do shortly. Which is a reminder: the concept of an excess return is a definition, and we get to decide which definition to use. If logs are more convenient, then we go back (as we did here) and compute excess returns in logs.

Here are the numbers, computed both ways. In levels, the mean short or riskfree rate is 2% ($r^1 = 1.02$). The mean excess return on equity is 5.7% ($r^e - r^1 = 0.057$). For later reference, the *Sharpe ratio* is the mean excess return divided by its standard deviation. (That's another definition, also useful in some contexts.) For equity, that's $0.0571/0.1873 = 0.3049$. (That's way too many digits, but I want to be clear about the calculation.) These numbers, or numbers like them, will serve shortly as targets for numerical examples of theoretical models.

Since many of our models are loglinear, we report similar numbers in logs. In logs, the mean short rate is 1.8% ($\log r^1 = 0.018$) and the mean equity premium is about 4.0% ($\log r^e - \log r^1 = 0.04$). I've rounded off most of these numbers to keep things simple.

We'll come back to the properties of consumption growth shortly.

3 The riskfree rate and equity premium puzzles

Now the question: Can we account for the 4% equity premium we observe in US data? How would we start? The question calls for a model, one capable of producing a similar premium. If we find one, then we have an explanation. We can then decide whether we find the explanation plausible or should continue our search for a better one.

We'll start in the obvious place: a representative agent economy with power utility. We give it a realistic distribution of consumption growth and (this is the short cut) tie dividends to consumption growth. We can come back later and see if that's a problem. We're following our own advice here: keep things as simple as we can.

We'll use two numerical examples to see how this might work. Both are similar to Mehra and Prescott's original work. In each case, we can look at the equity premium either in levels or logs. I prefer logs — you'll see why shortly — but we reported the evidence both ways.

Example (Bernoulli). Our first example is as simple as they come. At each date t , there are two states at the subsequent date $t + 1$. Call them $z \in \mathcal{Z} = \{-1, 1\}$ and give each a probability of one-half, $p(-1) = p(1) = 1/2$. Then let log consumption growth $\log g_{t+1} = \log(c_{t+1}/c_t)$ be

$$\log g_{t+1}(z) = \mu + \sigma z.$$

The good news is that the calculations are relatively easy with two states. The bad news is that they're opaque.

With this setup, the mean and standard deviation of log consumption growth are μ and σ , respectively. Looking at Table 1, we use the values $\mu = 0.02$ and $\sigma = 0.035$, which gives us a distribution we can argue is realistic.

Asset pricing follows from a pricing kernel and the dividends or cash flows of the relevant assets. With a representative agent and power utility, the pricing kernel follows from consumption growth:

$$m_{t+1}(z) = \beta g_{t+1}(z)^{-\alpha}.$$

The assets of interest are the riskfree bond, which has a dividend of 1 in all states, and “equity,” which has a dividend of $g_{t+1}(z)$ in state z . The riskfree rate is $r^1 = 1/q^1$ where

$$q^1 = E(m_{t+1}) = \sum_z p(z)m(z).$$

Let us say that equity is a claim to consumption growth. Its price is then

$$q^e = E(m_{t+1}g_{t+1}) = \sum_z p(z)m(z)g(z).$$

Its return is $g(z)/q^e$, so its mean return is $E(r^e) = E(g)/q^e$. The equity premium is $E(r^e) - r^1$. In this environment, each of these calculations is easily done in Matlab.

So what do we get? We set $\beta = 0.99$ to get started. If $\alpha = 2$, the riskfree rate r^1 is 1.0383, which well above our target of 1.020, and the equity premium 0.0025, which is well below our target of 0.057. We could fix the riskfree rate by raising β , but this has its limits. If we raise α to 5, the riskfree rate is 1.0995, which is even higher, and the equity premium rises only to 0.0067. If we take this range of α to be reasonable, we’re stuck.

We thus have two problems. One is what is often termed the *riskfree rate puzzle*: the short rate is too high. If we increase β to fix this, we end up with $\beta > 1$, which seems implausible. (And if we extended utility to more periods, we run into technical problems.) The second problem is the *equity premium puzzle*: we haven’t reproduced anything close to the equity premium we see in the data. Would larger values of α work? Would they be plausible if they did? It’s not clear, but such values do seem outside what we decided earlier fit our own sense of risk aversion.

[See Matlab program for computations.]

Example (lognormal). Our second example is based on a lognormal environment. The results are similar, but here we get to look at the solutions and see where they go wrong. Let us say that $\log g_{t+1} \sim \mathcal{N}(\kappa_1, \kappa_2)$. That gives us the pricing kernel $\log m_{t+1} \sim \mathcal{N}(\log \beta - \alpha\kappa_1, \alpha^2\kappa_2)$. We’ll look at the riskfree rate and equity premium in logs here, because that fits well with this example.

We’ll use a convenient shortcut, which I got from Andy Abel. Consider a claim to g_{t+1}^λ . If $\lambda = 0$, we get the riskfree bond, and if $\lambda = 1$ we get equity. Some people refer to $\lambda > 1$ as “levered equity” because the dividend is more sensitive to changes in output, as it would be with increased leverage. The price of this asset is

$$q(\lambda) = \beta E(g_{t+1}^{\lambda-\alpha}) = \beta \exp [(\lambda - \alpha)\kappa_1 + (\lambda - \alpha)^2\kappa_2/2].$$

That gives us log returns of

$$\begin{aligned}
\log r^1 &= -\log \beta + \alpha \kappa_1 - \alpha^2 \kappa_2 / 2 \\
E(\log r^e) &= -\log \beta + \alpha \kappa_1 - (\alpha - \lambda)^2 \kappa_2 / 2 \\
E(\log r^e - \log r^1) &= [\alpha^2 - (\alpha - \lambda)^2] \kappa_2 / 2 \\
&= \lambda(2\alpha - \lambda) \kappa_2 / 2 \\
&= (2\alpha - 1) \kappa_2 / 2 \quad \text{when } \lambda = 1.
\end{aligned}$$

We can see both puzzles right here. The riskfree rate r^1 is quadratic in α . At moderate values, it increases with α , so the riskfree rate will be too high. (You can add numbers to make this more precise.) But if α gets big enough, the impact of the variance term will bring it down again. In this sense, we can resolve the riskfree rate puzzle by choosing α really large. The equity premium, on the other hand, is strictly increasing in α . If we make α large enough, we can account for any equity premium we like. Using $\kappa_1 = 0.035^2$, we hit the equity premium of 0.0400 (in logs, remember) at

$$2\alpha - 1 = 2(0.0400)/(0.035^2),$$

or $\alpha = 33.15$.

Both examples make the same point: that we can't account for the observed equity premium unless we use a large value of α . Is $\alpha = 33$ reasonable? There's some debate about that, but our own thought experiment in class suggests it's more than a bit high. People with that kind of risk aversion won't be willing to take much risk, which is why it generates a large equity premium.

Where do we go from here? When other classes have discussed this, they had a number of good suggestions. Among them: (i) consider a more complex distribution of dividends; (ii) ditto consumption growth; (iii) use some kind of "friction" so that the risks faced by an individual are greater than those evident in aggregate consumption; and (iv) allow different preferences. All of these are good ideas, but my money's on (iii). The first one we'll rule out shortly. The others take more advanced tools than we have at present, but we may come back to them if we have time.

4 The Hansen-Jagannathan bound

If we think of the equity premium as a problem, the question is where its roots lie. The answer, in large part, is the pricing kernel. In this section and the next we derive bounds on the dispersion — or variability — of the pricing kernel. Observed risk premiums give us lower bounds on this dispersion, whatever it might be. With power utility, the point is that you need lots of risk aversion to get enough dispersion variability.

The first bound comes from Hansen and Jagannathan. They start with the no-arbitrage theorem: the return r^j on any asset j satisfies

$$E(mr^j) = 1. \tag{1}$$

If we take two assets, say j and 1, then the excess return $x = r^j - r^1$ satisfies

$$E(mx) = 0.$$

That's true for any two returns.

Expanding terms and applying the definition of the covariance gives us

$$E(mx) = E(m)E(x) + \text{Cov}(m, x) = E(m)E(x) + \rho_{mx}\text{Std}(m)\text{Std}(x).$$

Here ρ_{mx} is the correlation between m and x and Std is the standard deviation. Since the absolute value of the correlation is less than one, we have

$$\frac{|E(x)|}{\text{Std}(x)} \leq \frac{\text{Std}(m)}{E(m)}. \quad (2)$$

This is the HJ bound. It says that the Sharpe ratio (the left side) places a lower bound on the dispersion of the pricing kernel. Dispersion here is the ratio of the pricing kernel's standard deviation to its mean. The mean is close to one (the price of a one-period bond), so it's more or less the standard deviation.

We've seen, then, that observed Sharpe ratios place lower bounds on the dispersion of the pricing kernel. How do our examples work? I leave the calculations to you, but both of the examples from the previous section violate the bound with reasonable values of the risk aversion parameter α . That means that the problem is in the pricing kernel: there's no point trying other dividend processes, they won't solve the problem.

5 Entropy

The term *entropy* has been used in lots of situations, including thermodynamics, but its modern use in many fields follows from Shannon's classic application to information theory. Tom Sargent passed on this wonderful quote:

When Shannon had invented his quantity and consulted von Neumann on what to call it, von Neumann replied: "Call it entropy. It is already in use under that name and, besides, it will give you a great edge in debates because nobody knows what entropy is anyway."

The idea in most applications is that entropy is a measure of dispersion.

We define the pricing kernel's entropy $H(m)$ by

$$H(m) = \log E(m) - E(\log m).$$

Since \log is a concave function, Jensen's inequality assures us that $H(m) \geq 0$, with equality only if m is constant. It is, therefore, a measure of dispersion or variability. Another property: $H(\lambda m) = H(m)$ for any positive constant λ . [Show by applying the definition.]

Example (lognormal). Suppose $\log m \sim \mathcal{N}(\kappa_1, \kappa_2)$. Then

$$H(m) = (\kappa_1 + \kappa_2/2) - \kappa_1 = \kappa_2/2,$$

the variance over two.

This is not the definition you'll see elsewhere, so let's connect them. Recall that the pricing kernel is related to risk-neutral probabilities by $pm = q^1 p^*$ or $m = q^1 p^*/p$. From the properties of H , we have

$$H(m) = H(p^*/p) = -E \log(p^*/p).$$

Here and throughout, the expectation E is based on the true probabilities p . The quantity on the right is referred to as the *relative entropy of p with respect to p^** . If you'd like to know more, let me know and I'll point you to the classic references.

6 The entropy bound

Now that we've defined entropy, we can describe the entropy bound. It has a different structure from the HJ bound but a similar spirit.

We start again with the pricing relation (1). If we take the log of mr , Jensen's inequality tells us

$$E [\log(mr^j)] = E (\log m + \log r^j) \leq \log(1) = 0.$$

Rearranging terms gives us

$$E(\log r^j) \leq -E(\log m).$$

The highest possible mean log return, in other words, is $\log r = -\log m$.

That gives us the second term in entropy, but what about the first? We have

$$\log E(m) = \log q^1 = -\log r^1.$$

Together we have

$$E(\log r^j) - \log r^1 \leq \log E(m) - E(\log m) = H(m). \quad (3)$$

In words: excess returns place a lower bound on the entropy of the pricing kernel. Like the HJ bound, properties of returns give us a lower bound on the dispersion of the pricing kernel. Here dispersion is measured by entropy.

Thus properties of returns tell us something about the pricing kernel. Consider the lognormal case. If $\log m \sim \mathcal{N}(\kappa_1, \kappa_2)$, then an equity premium (in logs) of 0.04 gives us a lower bound on the variance κ_2 :

$$0.0400 \leq H(m) = \kappa_2/2.$$

With other distributions, entropy incorporates all the high-order cumulants of $\log m$. Recall that $\log m$ has the cumulant generating function

$$k(s; \log m) = \log E \left(e^{s \log m} \right).$$

The first term in the definition of entropy is therefore $k(1; \log m)$. If the cgf has the power series expansion

$$k(s; \log m) = \kappa_1 s + \kappa_2 s^2/2 + \kappa_3 s^3/3! + \kappa_4 s^4/4! + \dots$$

for some suitable range of s , then

$$H(m) = \kappa_2/2 + \kappa_3/3! + \kappa_4/4! + \dots$$

The first term is the lognormal term. The others illustrate the potential benefit of departing from normality, since they can increase entropy even when we hold the variance constant. Stan Zin refers to this as the *never-a-dull-moment conjecture*: if a model doesn't work, you can in principle fix it up by adding enough high-order cumulants. Whether that's reasonable is another matter, but it's an interesting illustration of the benefits of going beyond the normal distribution. Note in particular that positive skewness ($\kappa_3 > 0$) and kurtosis ($\kappa_4 > 0$) make positive contributions to entropy.

The κ_j 's here are cumulants of $\log m$, but with power utility, it's not hard to show that they're connected to cumulants of $\log g$:

$$\kappa_j(\log m) = (-\alpha)^j \kappa_j(\log g), \quad j \geq 2.$$

We see that for odd cumulants to make a positive contribution to entropy, the cumulants of \log consumption growth must be negative. Thus negative skewness in $\log g$ leads to positive skewness in $\log m$. Amir Yaron notes that the power of α allows small cumulants in \log consumption growth to become large cumulants in the log pricing kernel. We refer to that as *Yaron's bazooka* in his honor.

Before finishing, here's a calculation related to the equity premium. In the lognormal case, $\kappa_2(\log m) = \alpha^2 \kappa_2(\log g)$. The bound based on the equity premium therefore implies

$$H(m) = \alpha^2 \kappa_2(\log g)/2 \geq 0.0400.$$

With $\kappa_2 = 0.035^2$ (Table 1), that implies $\alpha \geq 8.08$. This is lower than our equity premium calculation, but then it's a lower bound.

Bottom line

The representative agent model has one big strength: it associates risk premiums with the cyclical behavior of output, profits, and dividends, which seems roughly right. Put simply: Assets that pay off most in good times, when consumption is high, have positive risk premiums. The numbers, however, are off. The equity premium, the Hansen-Jagannathan bound, and the entropy bound all point to variability of the pricing kernel as the key

issue for asset pricing models. Representative agent models with plausible degrees of risk aversion simply don't generate enough variability to account for the equity premium — and, presumably, lots of other assets with nonzero risk premiums.

Perhaps for this reason, financial professionals often use arbitrary pricing kernels designed to fit a set of asset prices well. These models don't tell us where risk premiums comes from, but they approximate observed asset prices reasonably well. We'll see examples of this kind of thing when we turn to option and bond pricing.

Practice problems

1. *Equity premium with Bernoulli consumption growth.* We work through a bunch of the computations from this chapter in a simple setting to make sure we understand how they work. We'll use the Bernoulli example from Section 3, where z takes on the values $\{-1, 1\}$ with probabilities $\{1/2, 1/2\}$. Log consumption growth is $\log g(z) = \mu + \sigma z$. Assets are valued by a representative agent with power utility, risk aversion parameter $\alpha = 5$, and discount factor $\beta = 0.99$.
 - (a) Use the values in the text for μ and σ . What is their rationale?
 - (b) What are the values of the growth rate g in each state?
 - (c) What values does the pricing kernel take in each state?
 - (d) What is the riskfree rate with these values?
 - (e) Define equity as a claim to the growth rate g . What is its price? Its return in each state?
 - (f) What is the equity premium in levels? What is equity's Sharpe ratio?
 - (g) What are the mean and variance of the pricing kernel m ? What is the maximum Sharpe ratio this economy can generate?
 - (h) What is the equity premium in logs?
 - (i) What is the entropy of the pricing kernel? How does it compare to the equity premium in logs?

Answer.

- (a) The values $\mu = 0.02$ and $\sigma = 0.035$ approximate the mean and standard deviation of log consumption growth in US data.
- (b) The growth rates are $g(-1) = 0.9851$ and $g(1) = 1.0565$.
- (c) The pricing kernel takes on the values $m(-1) = 1.0671$ and $m(1) = 0.7520$.
- (d) The price of a bond is $q^1 = 0.9095$, making the riskfree rate $r^1 = 1.0995$.
- (e) The price of equity is $q^e = 0.9229$, making the returns $r^e(-1) = 1.0675$ and $r^e(1) = 1.1449$.
- (f) The equity premium is $E(r^e - r^1) = 0.0067$. The Sharpe ratio is the excess return's mean divided by its standard deviation: $0.0067/0.0387 = 0.1732$.
- (g) The mean and standard deviation of m are 0.9095 and 0.1576. The maximum Sharpe ratio is $0.1576/0.9095 = 0.1732$; see HJ bound. Evidently equity hits the bound in this economy.

- (h) Using log returns, the equity premium is $E(\log r^e - \log r^1) = 0.0055$.
 - (i) Entropy is $H(m) = 0.0152$, which is well above the equity premium in logs. Evidently there's an asset with a higher return than equity; see entropy bound.
2. *Sharpe ratios.* Consider Sharpe ratios in a two-period representative agent economy. Endowment growth g is Bernoulli,

$$g = \begin{cases} 1.00 & \text{with probability } 1 - \omega \\ 1.10 & \text{with probability } \omega, \end{cases}$$

with $\omega = 0.3$. The representative agent has power utility with discount factor $\beta = 0.98$ and risk aversion $\alpha = 5$. Equity is a claim to g .

- (a) What is the pricing kernel for this economy? What are the state prices?
- (b) What are the price and return of a one-period riskfree bond?
- (c) What is the price of equity? What are the mean and standard deviation of its excess return? What is its Sharpe ratio?
- (d) What is the maximum Sharpe ratio for this economy?

Answer.

- (a) The pricing kernel is $m(z) = \beta g(z)^{-\alpha}$. Here we have $m = [0.9800, 0.6085]$. State prices are $Q(z) = p(z)m(z)$ or $Q = [0.6860, 0.1826]$.
- (b) The price of the bond is

$$q^1 = \sum p(z)m(z) = 0.8686,$$

which implies $r^1 = 1/q^1 = 1.1513$.

- (c) The price of equity is

$$q^e = \sum p(z)m(z)g(z) = 0.8868.$$

The returns are $r^e(z) = g(z)/q^e = [1.1276, 1.2404]$. The mean and standard deviation follow either from a brute-force calculation $[\text{Var}(x) = E(x^2) - E(x)^2]$ or related formulas for Bernoulli random variables. The mean and standard deviation of the excess return are 0.0102 and 0.0517. The Sharpe ratio is the ratio of the two: $0.0102/0.0517 = 0.1960$.

- (d) This is an application of the Hansen-Jagannathan bound. The maximum Sharpe ratio for this pricing kernel is the ratio of the standard deviation of the pricing kernel to its mean. Here we get $0.1702/0.8686 = 0.1960$. Our asset therefore hits the bound. That's something of an accident. It works because of the two-state structure, which means all returns are linear functions of the pricing kernel, and therefore perfectly correlated with the pricing kernel. Don't worry if that seems obscure to you.
3. *Sharpe ratios and leverage.* One of the convenient properties of Sharpe ratios is that they're invariant to leverage. Consider a portfolio consisting of fraction $a > 0$ in asset with return r^j and fraction $1 - a$ in a safe asset with return r^1 .

- (a) What is the return on this portfolio? The excess return over the riskfree rate r^1 ?
- (b) How does the excess return vary with a ?
- (c) What is the Sharpe ratio? How does the Sharpe ratio depend on a ? What happens if $a < 0$?

Answer.

- (a) The return is $r^p = ar^j + (1-a)r^1$ (p for portfolio). The excess return is $x = r^p - r^1 = a(r^j - r^1)$.
 - (b) The excess return is proportional to a : if we double a , then we double the excess return, for good and bad.
 - (c) The mean and standard deviation of the excess return are both proportional to a . As a result, a drops out of the Sharpe ratio. If we double a , we double the expected excess return, but we also double its standard deviation, so the Sharpe ratio stays the same. If $a < 0$, we reverse the sign of the Sharpe ratio. In words: if we have an asset with a negative Sharpe ratio, we simply reverse the trade and short the asset.
4. *Hansen-Jagannathan bound for lognormal pricing kernel.* Suppose the pricing kernel is lognormal: $\log m \sim \mathcal{N}(\kappa_1, \kappa_2)$. This doesn't fit naturally into the HJ bound, because the bound is based on moments of m rather than $\log m$. With a little work, however, we can connect the two.
- (a) What is the mean of m ? The variance?
 - (b) What is the maximum Sharpe ratio attainable from this pricing kernel?
 - (c) Consider an arbitrary distribution of $\log m$ with moment generating function $h(s) = E(e^{s \log m})$. Express the maximum Sharpe ratio as a function of h .

Answer. We'll attack the general case first and do the problem in reverse order.

- (a) The mean of m is

$$E(m) = E(e^{\log m}) = h(1).$$

Similarly, the variance is

$$\text{Var}(m) = E(m^2) - E(m)^2 = h(2) - h(1)^2.$$

- (b) From the HJ bound, the maximum Sharpe ratio is

$$\text{Var}(m)^{1/2}/E(m) = [h(2) - h(1)^2]^{1/2}/h(1) = [h(2)/h(1)^2 - 1]^{1/2}.$$

- (c) In the lognormal case, $h(s) = \exp(s\kappa_1 + s^2\kappa_2/2)$, so we have

$$h(2)/h(1)^2 = \exp(2\kappa_1 + 2\kappa_2)/\exp(2\kappa_1 + \kappa_2) = \exp(\kappa_2).$$

The maximum Sharpe ratio is therefore $[\exp(\kappa_2) - 1]^{1/2}$. For small κ_2 , this is approximately $\kappa_2^{1/2}$, the standard deviation of $\log m$.

5. *Entropy bound revisited.* The goal is to derive the entropy bound from a maximization problem. We'll do this in an arbitrary two-period economy with a finite set of states. Each state z has probability $p(z)$ and pricing kernel $m(z)$. An asset has returns $r(z)$ that satisfy the pricing relation

$$\sum_z p(z)m(z)r(z) = 1. \quad (4)$$

Our mission is to characterize the asset with the highest expected log return,

$$\sum_z p(z) \log r(z).$$

We'll refer to this as the “high-return asset.”

- (a) What is the entropy of the pricing kernel? Express it in terms of $m(z)$ and $p(z)$.
- (b) Use Lagrangian methods to find the returns $r(z)$ (one number for each state) that maximize the expected log return while satisfying the pricing relation (4). How is the return on the high-return asset related to the pricing kernel?
- (c) Show that the high-return asset attains the entropy bound.

Answer.

- (a) Entropy is defined by

$$H(m) = \log E(m) - E(\log m) = \log \sum_z p(z)m(z) - \sum_z p(z) \log m(z).$$

- (b) The idea is to maximize the expected log return with the pricing relation as a constraint. The Lagrangian is

$$\mathcal{L} = \sum_z p(z) \log r(z) + \lambda \left(1 - \sum_z p(z)m(z)r(z) \right).$$

The first-order condition for $r(z)$ is

$$p(z)/r(z) = \lambda p(z)m(z).$$

You can see here that there's an inverse relation between $r(z)$ and $m(z)$, but we need to eliminate the multiplier λ . If we multiply both sides by $r(z)$ and sum over z , we see that the left side is one and the right side is λ , so we must have $\lambda = 1$. That gives us the maximizing return

$$r(z) = 1/m(z).$$

We did this earlier using Jensen's inequality, but this is more constructive.

- (c) The entropy bound says

$$E(\log r - \log r^1) \leq H(m) = \log E(m) - E(\log m).$$

All we need to do is substitute. We have $r = 1/m$, so $E(\log r) = E(\log m^{-1}) = -E(\log m)$. The one-period rate is $r^1 = 1/E(m)$, so $\log r^1 = -\log E(m)$. That gives us

$$E(\log r - \log r^1) = -E(\log m) + \log E(m) = H(m).$$

(The E in front of r^1 is irrelevant here, because r^1 is a constant.)

6. *Expected returns in levels and logs.* We saw that the expected returns in Table 1 satisfy

$$T^{-1} \sum_{t=1}^T \log r_t^e = 0.0587 \leq \log \left(T^{-1} \sum_{t=1}^T r_t^e \right) = \log(1.0769) = 0.0741.$$

Show that this inequality always holds.

Answer. It follows from Jensen's inequality and the concavity of the log function. Use probabilities $1/T$ for every value of r_t^e . Put somewhat differently, the difference $\log E(r^e) - E(\log r^e)$ is the entropy of r^e , which is always nonnegative. My finance friends refer to this as a “convexity adjustment,” but the terminology always struck me as confusing.

7. *Disaster risk and the equity premium.* We add a third “disaster” state to our analysis of the equity premium and see how it changes our perspective. The key input is the distribution of log consumption growth,

$$\log g = \begin{cases} \mu - \sigma & \text{with probability } (1 - \omega)/2 \\ \mu + \sigma & \text{with probability } (1 - \omega)/2 \\ \mu - \delta & \text{with probability } \omega. \end{cases}$$

What's the idea? If $\omega = 0$, we're back to our symmetric two-state distribution. But if we choose a small positive value of ω and a “largish” $\delta > 0$, we have a “disaster” state that changes the distribution dramatically.

The question is what this does to the equity premium. As usual, we define equity as a claim to consumption growth g . We'll use the equity premium in logs,

$$E(\log r^e - \log r^1),$$

and aim at a target value of 0.0400 (4%).

- If $\omega = 0$, what values of μ and σ deliver the observed mean and variance of log consumption growth, namely 0.0200 and 0.0350²?
- Continuing with these values, suppose $\beta = 0.99$ and $\alpha = 10$. What are $\log r^1$ and the equity premium, $E \log r^e - \log r^1$?
- What is entropy? How does it relate to the equity premium you computed above?
- Now consider $\omega = 0.01$ and $\delta = 0.30$. (These numbers are based on a series of studies by Robert Barro and his coauthors.) With these numbers, what values of μ and σ reproduce the observed mean and variance of log consumption growth?
- With (again) $\beta = 0.99$ and $\alpha = 10$, what are $\log r^1$ and the equity premium, $E \log r^e - \log r^1$? How does it compare to your previous calculation?
- How does entropy differ between the disaster and no-disaster cases?
- How does entropy change if $\delta = -0.30$, so that the extreme state is good news rather than bad? Can you guess why?
- Optional, extra credit.* How much entropy is due to the following components: the variance of $\log m$ and odd and even cumulants collectively of order $j > 2$.

Answer. The idea is to show how changing the distribution in ways that produce negative skewness can increase risk premiums even if we keep the mean and standard deviation of log consumption growth the same. It's like a partial derivative result: vary skewness while holding the standard deviation constant.

- (a) The expressions for the mean and variance of $\log g$ are

$$\begin{aligned} E(\log g) &= \mu - \omega\delta = 0.0200 \\ \text{Var}(\log g) &= (1 - \omega)\sigma^2 + \omega(1 - \omega)\delta^2 = 0.0350^2. \end{aligned}$$

When $\omega = 0$, the mean is $\mu = 0.0200$ and the standard deviation is $\sigma = 0.0350$.

- (b) With these values, we have $r^1 = 1.1618$, $\log r^1 = 0.1500$, and $E \log r^e - \log r^1 = 0.0112$.
- (c) Entropy here is 0.0600. This is an upper bound on expected excess returns, so the model is evidently able to generate risk premiums greater than the equity premium.
- (d) When $\omega = 0.01$, we need to set $\mu = 0.0230$ and $\sigma = 0.0183$ to maintain the mean and variance at their sample values. See (a).
- (e) With these values, we have $r^1 = 1.0529$, $\log r^1 = 0.0516$, and $E \log r^e - \log r^1 = 0.0438$. We have a success! The equity premium goes up and is now above our target. In that respect, the disaster state is a useful innovation, although need a large risk aversion parameter for it to work.
- (f) Entropy rises, too, to 0.1585. Yaron's bazooka in action!
- (g) If we switch the sign of δ , entropy falls to 0.0371. Evidently positive skewness in consumption and dividend growth isn't helpful.

This reflects an issue we've seen before. With power utility, people like positive skewness (lottery tickets) but dislike negative skewness (disasters). To take on negative skewness, they demand large risk premiums. We see that reflected here. With negative skewness, entropy is high, with positive skewness it's low. Skewness here means (roughly) an asymmetric distribution, which might be reflected in negative cumulants of all orders above the first one.

Table 1. Properties of US real asset returns and consumption growth. The numbers are from Shiller’s [website](#), updated. Data covers the period 1889-2009, annual. Returns are real: nominal returns minus inflation. Equity is the S&P 500 and its predecessors. Consumption is per capita. The calculations are done with the Matlab program `Shiller data.m`, posted on the course website.

| Asset | Mean | Std Dev | Skewness | Ex Kurt |
|-------------------------------------|--------|---------|----------|---------|
| <i>Properties of levels</i> | | | | |
| Consumption growth g | 1.0207 | 0.0356 | −0.1886 | 0.9434 |
| Short rate r^1 | 1.0198 | 0.0580 | 0.4174 | 2.8122 |
| Equity return r^e | 1.0769 | 0.1846 | −0.0898 | −0.1035 |
| Excess return $r^e - r^1$ | 0.0571 | 0.1873 | −0.2095 | 0.2809 |
| <i>Properties of logs</i> | | | | |
| Consumption growth $\log g$ | 0.0198 | 0.0350 | −0.3433 | 1.1112 |
| Short rate $\log r^1$ | 0.0180 | 0.0566 | 0.0380 | 2.3976 |
| Equity return $\log r^e$ | 0.0587 | 0.1795 | −0.6134 | 0.4311 |
| Excess return $\log r^e - \log r^1$ | 0.0407 | 0.1812 | −0.7157 | 0.9065 |

Figure 1. US real asset returns v. consumption growth, 1889-2009. Same data as Figure 1.

