Introducing super-risk
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Introduction

The concept of risk is a natural topic for a symposium on decision theory and the law. Laws regulate decision-makers and many decisions are made in conditions of risk. Since, plausibly, proper regulation needs to be grounded in a proper understanding of what is being regulated, it follows that risk itself needs to be a topic of discussion. This applies to the regulation of individuals, as putatively rational decision-makers who operate in risky environments. It also applies to much larger scale forms of legal regulation, such as the regulation of the financial services industry (to take a topical and much-discussed example).

Discussion of financial regulation often boils down to calculation of what counts as acceptable levels of risk (as for example in imposing capital requirements on banks). These discussions and calculations take place within a fairly standard theoretical understanding of what risk is. I will explore that understanding in this paper. My examples are almost all from finance rather than the law, although I am in fact almost equally ignorant in both fields. But I hope that others better qualified than I am will be able to make connections in the discussion.

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Ideas about risk circulate widely in financial markets, universities, and the popular press. There are people who make their living as risk managers and many others who employ risk management tools in their daily business. Risk managers think of risk as something that can be measured, manipulated, and, well, managed.

Despite all this focus on risk, there is a fundamentally important type of risk that has been systematically ignored. I call it super-risk. Super-risk doesn’t behave in the right sort of way for standard risk management techniques. This is, I would conjecture, one of the root causes of market turmoil and investment catastrophe, as experienced in financial crises and stock market crashes – most recently in the sub-prime crisis and associated market meltdown.

My aim in this paper is to give an intuitive sense of the phenomenon. As often happens, in order to appreciate what super-risk is, we need to start with what it is not. I'll start with an important distinction economists make between two
types of decision-making. Economists call these decision-making under risk and decision-making under uncertainty.

The distinction, which goes back to the economist Frank Knight, is profoundly important, but I find the terminology potentially confusing. For most people, risk and uncertainty are related concepts, not opposed ones. In everyday speech, what makes something risky is that there is uncertainty about how it will turn out. This can make it hard to see what Knight was getting at. For this reason, I will suggest that we change Knight’s terminology. What Knight calls decision-making under risk I will call actuarial decision-making, for reasons that will emerge in the next section.

Knight’s distinction

Let me begin with some simple examples to get an intuitive grip of Knight’s distinction. Here are 4 cases that would typically be described as an individual grappling with risk.

An investor is deciding whether to buy shares in a particular company. A woman is agonizing over whether to leave her job and start a business. A grandfather is not sure whether to buy his granddaughter a UK government premium bond that, instead of paying a fixed rate of interest, is entered every month into a lottery with tax-free prizes. An insurer is calculating what the premium should be for an insurance policy on your life with your husband and children as beneficiaries.

My first question is whether these decisions are all risky in the same way. In some of these cases the person involved can, in principle, make a fairly precise estimate of how things are likely to turn out. By “fairly precise” I (and Knight) mean that numbers can be assigned to the probabilities of the different possible outcomes. Numerical probabilities are numbers between 0 and 1. An event with probability 0 is impossible. An event with probability 1 is inevitable. An event with probability 0.5 is as likely to occur as not to occur. And so on.

When we make decisions we need to think about the different courses that events could take. Let’s call these possible conditions. A decision will have a different outcome depending on which of the possible conditions ends up holding. If I place a bet on the toss of a fair coin then there are two possible conditions – it lands heads or it lands tails. The outcome of my bet will depend upon which condition holds. So, for example, if I bet heads and the condition is heads, then I win.

If we can assign a numerical probability to each of the possible conditions then we are, according to Knight, in a case of decision-making under risk. Tossing a coin is a classic example. We know that the chance of a fair coin
coming up heads (or tails) is 0.5. The premium bond and life insurance cases involve the same kind of decision-making. Here’s why.

The grandparent thinking about the premium bond has, let’s say, two alternative courses of action. He can buy the premium bond or keep the money in the bank. If he keeps the money in the bank then the outcome is that it will earn interest at a certain rate. If he buys the premium bond then the outcome depends on the bond’s chances of winning one of the many prizes on offer in the lottery.

Fortunately, these chances can be precisely calculated, as the UK government adjusts the prizes in the lottery so that each pound invested in premium bonds will over time return an average return of 1.5% per year (as of March 2012). So the decision is fairly straightforward. It ultimately boils down to a comparison between the rates of return on bank accounts and on premium bonds.

It is true that bank savings accounts offered a guaranteed return, whereas premium bond lotteries don’t – you might win nothing at all in the lottery, or you might win a million pounds. But, from Knight’s point of view, this variability doesn’t introduce a new kind of risk.

We need to think about the premium bond and the savings account in terms of the return we can expect from each of them. This expected return is fixed by what you will receive in the different conditions, together with the probabilities of each condition holding. In the premium bond lottery, there is a condition associated with each different prize. In savings accounts, in contrast, there is only one condition – the condition in which you receive the guaranteed interest. The theory behind this is the theory of expected utility- the basic currency of decision theory.

The life insurance case has the same basic structure. Life insurers have access to actuarial tables. These are huge databases of mortality rates. An actuarial table shows the probability that a given person of a given age will die before their next birthday. Actuarial tables can be produced for given populations. There are different actuarial tables for men and women. Tables can also be constructed for different socio-economic groupings and populations with different health characteristics (smokers vs non-smokers, for example).

So, an insurer writing a life insurance policy is in a much stronger position (information-wise) than the person buying the policy. Actuarial tables have been built up over many decades. Insurers are pretty confident that their predictions are accurate. With an actuarial table in hand an insurer can calculate a premium that would on average be profitable for her company, given the likelihood that people like you will die within the term of the policy and the payout that would
then have to be made. The calculations are fairly complex – but that’s what actuaries are for.

Knight’s second category of decisions are those where decision-makers are not in any position to assign numbers to the probabilities of different outcomes. In these types of decision, decision-makers know only what the outcomes of the different actions might be. They are not in the dark about what might happen. But they are in the dark about how likely the different outcomes are.

The case of the woman thinking about whether to leave her job and start a business seems to me to be a clear case of decision-making under uncertainty. You may think that staying in her job has a fairly predictable outcome. But even here there are many things to take into account. What happens if the company she works for goes bankrupt; or gets taken over; or reassesses its strategic priorities in the face of economic headwinds etc?

But even if you are comfortable assigning numbers to these different conditions, think about all the different ways that things could turn out if she quits her job. Even if we simplify things by thinking of this in terms of only two possible outcomes (the business succeeds or the business fails), there are so many imponderables that trying to assign numbers seems a fool’s errand.

There are no actuarial tables for small business start-ups – and nor could there be. Small businesses are all very different. There is only a small number of ways for a small business to fail – all of them boiling down more or less to the business taking in less money than goes out. But the problem is that there is indefinitely much variation in the factors that can cause a small business to fail. There might be problems with its business plan, with its sources of financing, with its location, or with its staff. And this is even before we start to think about the potential impact of macroeconomic factors, such as the rate of inflation or the health of the local economy. It would be brave to the point of foolhardiness to try to condense all this down into a single number.

(In the interests of full disclosure I should say that there is an influential group of statisticians and decision theorists who hold that a rational agent should always be able to assign numerical probabilities to outcomes. These are the followers of strict Bayesianism. I am not a strict Bayesian. Even as an unattainable ideal it does not seem to me desirable to require a rational agent to have a unique probability function. This is one lesson to be derived from the so-called Ellsberg paradox, which it turns out is not a paradox at all for non-Bayesians.)

So, to take stock, we began with four examples of individuals grappling with risk in financial decision-making. The examples fall into two groups. In the first group decision-makers have powerful tools to work with. They have
information about the probabilities with which different possible outcomes might occur. The premium bond and life insurance examples fit this description. I call these cases of actuarial decision-making.

Things are very different, however, for the woman leaving her job to start a new business, however. She may know what she stands to gain and what she stands to lose. But she is in no position to assign numerical probabilities. Knight's terminology seems very apt. She is making a decision under conditions of uncertainty.

The distinction between actuarial decision-making and decision-making under uncertainty has fundamentally to do with risk. In both types of case decision-makers confront risk. They confront both upside risk and downside risk. Some conditions have favorable outcomes. Others less so. The crucial difference is whether the risk can be quantified, whether it can be measured. Actuarial decision-making involves measurable risk. Decision-making under uncertainty does not.

Measuring risk in financial markets

We have looked at three of the four cases we began with. But what about the fourth? Let's focus on the investor thinking about buying shares in a particular company. How should we think about this type of decision-making?

The orthodoxy in the financial world, both in theory and in practice, is that investment decisions are basically actuarial. Risk is something that can be measured and managed. There are many different models for valuing companies and, more generally, for valuing portfolios. These models have built into them tools for measuring the different types of risk that an investor faces.

Many of these models are variations on something called the Capital Asset Pricing Model (CAPM). The CAPM is a way of calculating how much investors should be compensated for the risk that they run in buying a particular financial asset. The basic idea is very intuitive. The more risk you run, the greater the return that you are justified in expecting from the asset. And the return that you can expect from the asset needs to be reflected in its price.

But of course in order to apply this intuitive idea we need a way of measuring risk. In order to get a number out, we need to put numbers in. So, in order to work out the price of the asset we need a way of assigning numbers to the risk that an investor runs in owning an asset.

In the CAPM risk and return are intimately connected. A correctly-priced asset will yield a return that reflects the risk the investor is taking on. The greater the risk, the higher the return. The lower the risk, the lower the return. So, the
first step in understanding the CAPM is to understand two fundamental benchmarks. These benchmarks are the starting-points for working out how much you need to be compensated for holding a particular asset. They are

**Benchmark 1 = the risk-free rate of return.** This is the return that an investor can expect to receive without running any risk at all. The risk-free rate of return is standardly measured by interest rates on US Treasury bills of appropriate duration, or some equally secure investment.

**Benchmark 2 = the expected market rate of return.** This is the return that the market as a whole is expected to yield. This might be measured in terms of the expected return of some asset designed to track the behavior of the entire stock market – an index fund tracking the Standard and Poor 500 in the US, for example, or the Financial Times All Share Index in the UK.

If we subtract benchmark 1 from benchmark 2 we get what is known as the *market risk premium*. This is the extra return that we can expect for taking on the risk associated with holding the market, as opposed to sitting safely with Treasury Bills, or government-guaranteed savings accounts. If, for example, the return on a 2 year Treasury Bill is 3% and the expected return on, say, the Barclay’s corporate bond index is 7%, then the market risk premium is 4%.

In essence, valuing a particular risky asset is identifying the correct risk premium for that asset. We know what the risk-free rate of return is – we know what return we can get without running any risk at all. So what we need to know is how much extra return to expect from holding the risky asset.

One obvious question to ask is: How risky is this asset relative to the market as a whole? If the asset is less risky than the market, then the risk premium for the asset should be less than the market risk premium. If, on the other hand, the asset is riskier than the market, then it should have a higher risk premium.

This is where the beauty of the CAPM comes in. It gives a way of measuring the riskiness of a given asset relative to the riskiness of the market as a whole. Once we do that we can use the market risk premium to work out what return we should expect from our risky asset.

The key idea behind measuring risk in the CAPM is that the risk of an asset is measured in terms of its volatility. The more volatile an asset is, the risker it is. This imagine two stocks, both of which increase in price by 5% over the course of a year. Suppose that the price of one stock increases steadily over the year, while the other gyrates wildly over the same period, going from a high of +15% to a low of –15%. It is natural to think that the second stock is riskier.
than the first. For one thing, the more volatile it is the greater the chance that if you need to cash in early you will end up taking a loss.

If we know how volatile the market as a whole is, and also how volatile the risky asset is, then we can work out the volatility of the asset relative to the volatility of the market. If the asset is more volatile than the market then it is riskier than the market – and if less volatile then less risky. Let’s call this the asset’s relative volatility.

A measure of relative volatility is almost enough to allow us to work out the return we should expect from our asset – that is, the percentage of the amount invested that an investor holding that asset can expect to gain (or lose). Intuitively, the expected return should be determined by the market risk premium and the volatility. If the asset is more volatile than the market, then the expected return should be higher than the market risk premium – and if it is less volatile, then it should be lower. In other words, we should be paid more for holding an asset that is riskier than the market than we get paid for holding the market.

The only thing missing is a way of representing how closely related the risky asset is with the market as a whole. This is sometimes called the correlation coefficient between the return on the asset and the return on the market. The closer the correlation, the more importance we need to attach to the relative volatility. The correlation can be represented by a number between 1 and –1. If the correlation is 1, then the asset and the market are perfectly correlated – they move up and down together. If the correlation is –1, then they are inversely correlated – one goes up exactly when the other goes down.

Combining relative volatility and the correlation coefficient gives what is known as the beta of a risky asset. The beta of a stock is standardly taken to be a measure of how risky the stock is relative to the market as a whole. This allows us to calculate the return we should expect from the asset we are trying to value. In order to calculate the expected return we start with the risk-free rate – since that’s what we can get anyway. We then add to it the rate that we get by multiplying the market risk premium by the asset’s beta.

That, in essence, is the thinking behind the Capital Asset Pricing Model. The basic ideas are:

1. The price of an asset is fixed by the return that can be expected from it.
2. The expected return is fixed by how risky it is relative to the market as a whole.
3. The asset’s riskiness relative to the market as a whole is fixed by
   a) How volatile it is relative to the volatility of the market
   b) How correlated its returns are with the returns of the market
I have presented the CAPM as informally as possible. But the reason the model is so powerful and has been so influential is that there are ways of assigning numbers to each of the crucial parameters – to the relative volatility of the risky asset and to its correlation coefficient with the market.

How do we calculate relative volatility and correlation coefficients? We only have access to historical data. So that’s all we can use. The relative volatility of two assets is typically calculated by comparing their individual volatility ratings over a given historical period. One very common way of looking at how volatile an asset is over a particular period of time is to look at how much it diverges from its average price during that period. This is what statisticians call standard deviation.

Suppose, for example, that you are interested in the volatility of shares of Main Street Bank over a 12-month period. The first thing to do is work out the average price of a share for that period. Then you need to decide how fine-grained you want your volatility analysis to be. Are you interested in monthly fluctuations? Weekly? Daily? Or perhaps even more fine-grained than that – hourly, for example?

Suppose that you are interested in day-to-day volatility. Then for each day in the year you can measure the gap between the price on that day (perhaps the price at closing) and the average price over the 12-month period. If on most days the share price is only a little above or below the average price, then Main Street Bank stock is not very volatile. But if there are many days when the share price is a long way above or below the 12-month average, then it is highly volatile. Calculating the standard deviation is an easy way of measuring the degree of volatility (particularly if you have a spreadsheet).

So, suppose you know the historical volatility of Main Street Bank and the historical volatility of the market (say, the Standard and Poor 500) and you want to work out their relative volatility. All you need to do is to divide the first by the second. The relative volatility of Main Street Bank and the S & P 500 over a given period is given by the ratio of their individual volatilities over that period. And so, if the volatility of a financial asset is measured by that asset’s standard deviation, then we have any easy and precise way of measuring relative volatility.

The correlation coefficient is also not too hard to calculate, although the calculations are a little harder to describe. As mentioned earlier, the result of the calculations is a number between 1 and −1. If the correlation coefficient is 1 then the two assets are perfectly correlated. Perfectly correlated assets move perfectly in step with each other. When one goes up or down, so does the other. If the correlation coefficient is −1, in contrast, they are exactly inversely correlated. This means that when one goes down by a certain amount, the other goes up by that same amount.
So, putting all this together, we can see how the Capital Asset Pricing Model makes certain types of investment decision look very much like instances of actuarial decision-making. We can assign numbers to measure the risk and use those numbers to arrive at a view of the correct price for the asset. And the CAPM is just an example. There are many other models and variations upon models, all with the same aim – to find a way of measuring risk and to show how those measurements can be used to make investment decisions.

*From risk to super-risk*

We need a name for models of financial decision-making that present it as a form of actuarial decision-making. Let’s call them *actuarial models*.

All actuarial models of financial decision-making are based on a single basic assumption. This is the assumption that historical measures of key factors such as volatility are a good guide to those factors in the future. I will call this the *projectability assumption*, because it is the assumption that historical measures will project into the future.

If the projectability assumption for a given actuarial model holds then using that model to make decisions is an instance of actuarial decision-making. But what if the projectability assumption doesn’t hold? What if historical measures of, say, volatility and correlation do not project into the future?

If the projectability assumption fails, then all bets are off. Your risk measures and correlation measures are purely retrospective. They tell you how assets have behaved in the past, but give no guide as to how they might behave in the future. In this case your investment decisions would not be actuarial at all. They would be much closer to what Knight called decision-making under uncertainty.

But the financial decision-maker trying to apply, say, the Capital Asset Pricing Model when the projectability assumption fails is not in exactly the same position as someone who is knowingly making a decision under uncertainty. The point about making decisions under uncertainty is that you, the decision-maker, know that you cannot assign numbers to the different outcomes. So you know that you have to take a different approach. You might, for example, adopt a minimax strategy. The minimax strategy tells you to look at the worst-case scenario for each option and to choose the option that has the least bad worst case scenario.

But someone trying to apply the CAPM when the projectability assumption fails would only be in this position if they knew that the historical measures were
not going to project into the future. And of course the decision-maker can’t know this – any more than they can know that the historical measures are going to project into the future. Decision-makers can certainly measure how well the model has projected into the future in the past – but not whether that historical projectability will continue.

Look at it from the point of view of the decision-maker. The decision-maker has no idea whether the assumption holds or not. And so, as an immediate consequence, they do not know which kind of decision-making they are engaged in. They do not know whether they are operating under conditions of risk or under conditions of uncertainty.

This is what I call decision-making under super-risk. It arises only when there is an appearance of decision-making under risk. It arises only for decision-makers who try to project historical measures of risk (and other financial variables) into the future.

Projecting historical measures into the future gives a pattern. If a particular financial entity turns out to fall under the pattern then we can use the generalization to predict its behavior. If that occurs, and if the historical generalization is sufficiently precise, then at the moment of making the prediction we are in a situation of actuarial decision-making.

But if, on the other hand, the financial entity turns out not to fall under the pattern, then we are in a completely different situation – a situation closer to decision-making under uncertainty, but much more dangerous, because it carries with it the illusion of actuarial decision-making. Which situation are you in? You’ll find out – but unfortunately only with hindsight. At the moment of making the prediction you are either making a decision under risk or making a decision under uncertainty. But you can’t tell which. And that, in a nutshell, is decision-making under super-risk.

**Understanding super-risk**

The problem of super-risk is generated by very general features of certain types of decision-making. These general features are very prominent in financial markets and financial information.

To appreciate what these general features are we need to think a little more abstractly about generalizations and patterns. (For present purposes we can just take generalizations to be descriptions of patterns. Patterns are regularities in the world.) Correlation coefficients and measures of relative volatility are generalizations describing patterns.
When we use a generalization to predict how some object will behave, or how some event will turn out, we are assuming that the object or event is relevantly similar to the objects or events in the pattern that the generalization describes. This is something we do all the time. It is no exaggeration to say that our daily life depends upon constantly applying what I have already called the projectability assumption – the assumption that patterns that we have identified in the past will project into the future.

Let’s take an example from the world of investing – the so-called Dogs of the Dow investment strategy. This is a classic example of projecting a historical pattern into the future.

The Dogs of the Dow strategy is based on the observation that, over a certain number of years, large, blue chip companies with a high dividend yield have outperformed on an annual basis their peers with lower dividend yields. (The dividend yield of a share is calculated by dividing the dividend per share by the price of the share – it represents the percentage of the share price that is returned each year to the investor in the form of a dividend payment.) The strategy tells you to renew your portfolio completely at the same time each year. You should simply buy the 10 stocks in the Dow Jones Industrial Average with the highest dividend yield.

Let’s think about the different things that might go wrong here.

The first potential problem is that the observed data could turn out to be purely a coincidence. It might be that when we look at a wider set of data we see that the claimed relationship between relative dividend yield and performance simply fails to hold. It just happened to be the case, for a limited sample and over a limited period, that the outperforming blue chip companies had a high dividend yield. But there was no real relationship between their performance and their relative dividend yield. The companies didn’t outperform because they had a high dividend yield.

There is nothing mysterious about the possibility of this kind of error. It is just plain, old-fashioned risk – the risk that you have mistaken a coincidental correlation for a genuine, causal connection. Statisticians have developed sophisticated techniques for separating causation from correlation and for distinguishing genuine generalizations from spurious ones. I have no quarrel with statistics.

Typically in what follows I will assume that we are dealing with patterns and generalizations that have the explanatory property. By this I mean generalizations that track genuinely existing patterns. Generalizations with the explanatory property typically hold in virtue of causal connections. If the generalization underpinning the Dogs of the Dow strategy has the explanatory
property, this is because the high relative dividend yield plays a causal role in the Dogs of the Dow outperforming the other companies in the index.

But there’s another way that things can go wrong. Any two companies might be similar along one or two dimensions. They might both be companies with a high dividend yield, for example. But they will certainly be dissimilar along many dimensions. A strategy like the dogs of the Dow strategy might go wrong when applied to a specific blue chip company with a high dividend yield because one or more of the dissimilarities trumps the similarity. This holds even if the generalization has the explanatory property.

Let me spell this out in more detail. The first thing to emphasize is that I am assuming, for the sake of argument, that the Dogs of the Dow strategy is based on a genuine generalization. This means that it captures more than just a correlation. It is not just that the companies with a high relative dividend yield have outperformed the index. They have outperformed the index because they have a high dividend yield. But of course there are other contributing factors. The companies from whose performance the Dogs of the Dow strategy has been extrapolated resemble each other in some respects (including high relative yield), but not in others.

If an actuary says that smokers of a given age are more likely to die in the next twelve months than non-smokers of the same age, then we can be reasonably confident that smoking is the key contributing factor to the difference in life expectancy. Life insurers typically don’t have to ask very many more questions before fixing a price for the policy. The reason, of course, is that they (and we) have a pretty clear view of the machinery that leads from smoking to a lower life expectancy. We understand the health consequences of smoking, and how they impact mortality rates.

But the same doesn’t hold for companies in the DJIA and their relative dividend yields. There is nothing here corresponding to our medical understanding of how smoking contributes to cancer, emphysema, cardiovascular disease, and so on. Even if we assume that there is a historically robust dogs of the Dow phenomenon, our understanding of why it might occur is fundamentally different from the actuarial case. We know that relative dividend yield is a causal factor, but we have no idea what the other causal factors might be. And this is not very surprising, given the massive differences between the companies involved.

This means that we cannot be confident that the robust generalization we have identified in the past will carry over to the case to which we are trying to apply it. There remains the possibility that the new case will prove to be a counter-example, not an instance – even though the generalization is tracking a causal connection.
This is why decision-making in financial markets is so often decision-making under super-risk. Decision-makers are often working with generalizations that they have good reason to think have the explanatory property – generalizations that are not mere coincidences; generalizations that hold in virtue of real causal facts about the world. These generalizations typically make it seem that decisions are being made under actuarial conditions – that numbers can be assigned to the probabilities of different outcomes, and that risk can be measured.

This is a perfectly reasonable way to proceed – to the extent that you have evidence that you are working with patterns that have the explanatory property. But of course it rests upon the assumption that explanatory patterns will project into the future. Or, to put it another way, it rests upon the tacit assumption that generalizations that have the explanatory property also have the projectability property.

In cases of actuarial decision-making this assumption is well-founded. Actuarial generalizations project to new cases. If you have good evidence that a particular factor (say, smoking) has had a particular effect (say, decreasing life expectancy) in the past, then that gives you license to make predictions about the future. You can use those predictions to write your insurance policies with confidence (assuming that you write sufficiently many of them for the statistics to work in your favor).

The same typically holds in the physical sciences. If we have evidence that some apparent generalization in physics, say, fails to project to new cases then we should suspect that we haven’t really got a generalization at all. We’ve really just mistakenly identified coincidence and correlation as a real pattern. The explanatory property doesn’t hold. (There may be some complex scientific phenomena that cannot be understood in terms of actuarial generalizations. Climate change is a plausible example. But much of science, particularly basic science, is actuarial.)

So, in actuarial generalizations (as in many types of scientific generalization) the explanatory property and the projectability property stand or fall together. But this doesn’t generally hold in the financial markets. Certain distinctive features of how financial markets work break the link between the explanatory property and the projectability property. And so we end up in super-risk – the situation of not knowing whether we are making decisions under actuarial conditions or under uncertainty.

What are these features that break the link between the explanatory property and the projectability property? Let me sketch out just one.

_How generalizations in financial markets can undermine themselves_
It is a basic fact that patterns in the behavior of financial assets can be self-destructive. When investors notice the patterns and start to act upon them, their very actions can cause the patterns to cease to hold. The Dogs of the Dow strategy is a case in point.

If investors realize that the Dogs of the Dow will outperform their companions with a lower dividend yield, then they will adopt the investment strategy of buying those underappreciated and overperforming companies. This will drive their share price up and the end result will be that they stop being underappreciated and overperforming. There is some evidence that this is what actually happened to the Dogs of the Dow strategy after Michael O’Higgins first proposed it in 1991.

This phenomenon works both ways. If you think you have spotted an anomaly in the market you would be wise to consider the probability of other people spotting the very same anomaly. Unless you are doing something illegal the information you have is shared by other investors. So you should consider the possibility that there isn’t an anomaly there at all – because, if there were one, the market would already have closed it down. The efficient markets hypothesis generalizes this type of argument.

In a sense this phenomenon is not very mysterious. It is simply an example of what is often called the principle of no arbitrage – the principle that markets will close down any opportunity for a risk-free profit as soon as it appears. There is a related phenomenon in economics and social policy. Goodhart’s Law states that when policy-makers explicitly target a given economic indicator (such as, e.g., a given level of inflation) this changes its indicator function (e.g. what it tells us about unemployment). In any case, neither of these are examples of super-risk.

But nonetheless the Dogs of the Dow example does illustrate a very fundamental fact about financial markets. Financial markets move the way they do because of how investors behave. Investors behave the way they do because of how financial markets have moved in the past, and how they expect them to move in the future. This gives rise to a feedback loop that George Soros has labeled reflexivity. Here is how Soros describes reflexivity:

In situations that have thinking participants, there is a two-way interaction between the participants’ thinking and the situation in which they participate. On the one hand, participants seek to understand reality; on the other they seek to bring about a desired outcome. The two functions work in opposite directions: in the cognitive function reality is the given; in the participating function, the participants’ understanding is the constant. The two functions can interfere with each other by rendering what is
supposed to be given contingent. I call the interference between the two functions “reflexivity”. I envision reflexivity as a feedback loop between the participants’ understanding and the situation in which they participate, and I contend that the concept of reflexivity is crucial to understanding situations that have thinking participants. (Soros 2003, p. 2)

Soros has written very illuminatingly about the reflexivity of financial markets – and has also profited from it rather impressively. But I’d like to take his basic idea in a new direction, because it seems to me that reflexivity is one of the fundamental sources of super-risk.

Detecting historical patterns can lead investors to behave in certain ways. This is the first part of Soros’s feedback loop between information and participation. But then, and this is the second part of the loop, that behavior can fundamentally alter the basis for the generalization – participation can change the information base.

The run-up to the recent financial crisis provides a very clear illustration of this. Think about the pricing of mortgage-backed securities – securities that are backed by packages of mortgages on residential or commercial properties. As is by now very well-documented, the pricing of these securities (before they became known by their current name of “toxic assets”) was determined by the risk of the underlying assets defaulting. This risk was typically measured with reference to historical default rates.

This historical data allowed originators and buyers of mortgage-backed securities (and, for that matter, the rating agencies) to become convinced that they were engaged in actuarial decision-making. The models for pricing mortgage-backed securities allowed those securities to be sliced and diced into different layers or tranches, each yielding a different rate of return corresponding to a different level of perceived risk.

What happened next is well-known. Banks and mortgage companies started both selling mortgages to individuals who would never previously have qualified for loans and offering new types of mortgage products. They did so in part because they were confident in the historical default rates (in the percentage of mortgage loans that ended up in default) and in the projectability of those default rates into the future. This confidence reinforced the behavior that had the direct result of ensuring that the historical rates did not project. The end result, to cut a long story short, was that default rates ended up far above their historical levels – and mortgage-backed securities turned into toxic assets.

This illustrates how the reflexivity of financial markets can lead generalizations and patterns to undermine themselves. Mortgage companies and securitization bankers correctly identified a robust historical pattern of repayment
and default in residential and commercial mortgages. They assumed that this pattern would project into the future and fed it into their models. This had the direct consequence that the pattern undermined itself. The mortgage industry eventually discovered that they were working with a pattern that had the explanatory property but not the projectability property.

**Looking forward**

Investment is a process of making educated guesses about the future. The stock in trade of those educated guesses is perceived similarities and potential patterns. The complexity of the financial world and the ingenuity of its inhabitants have created almost endless possibilities for perceiving similarities and identifying patterns. These similarities and patterns are often numerically precise.

So, from the perspective of the individual investor, and indeed of the market as a whole, investment can all too easily have the appearance of what Knight would call decision-making under risk – and what I prefer to call actuarial decision-making. It looks as though we are allocating assets and purchasing securities on the basis of numerically determinate and well-grounded estimates of what the future will bring.

But that is a mistake. Our decision-making is often not actuarial. Instead it is decision-making under super-risk. This occurs when we are sure that we have identified precise patterns in past behavior – e.g. the past behavior of financial entities. These patterns can be made numerically precise using the tools that are the financial analyst’s stock in trade – expected return, beta, dividend yield, and so on. But the apparent numerical precision may flatter to deceive. We are in a position of super-risk because we have no way of knowing whether these patterns have the projectability property. If they do have the projectability property, then our decision-making is actuarial. But if they don’t, then we are making a decision under uncertainty. From where we stand, there’s no telling which situation we are in.

Ordinary risk (of the sort that an actuary confronts on a daily basis) can be measured and tamed. If I write a single insurance policy then I may easily get badly burned. My actuarial table won’t protect me against one-off unlikely events. But if I write enough policies, and do my sums correctly, then I on balance I am likely to come out ahead (the actuary’s skill lies in working out what count as “enough” and “on balance”).

Can super-risk be tamed in this way? My instinct is that it cannot. But that’s a topic for another time. My principal aim in this paper has been to introduce an important concept that has so far been neglected both by decision theorists and by lawyers, despite its relevance in a number of the areas where
decision theory and the law intersect. I look forward to hearing your thoughts and comments.