DEFINING, MEASURING, MANAGING, AND FACING RISK†

Thomas Root*

The Dean asked me to speak about managing, defining, and assessing risk from an academic perspective and to think a little bit more about how we model risk, what types of things we do with risk, and how we actually build from these probability ideas to which you keep hearing people refer. Is risk just a probability? Or is it something else? How does it come about?

As an economist who teaches finance, my comments are going to be directed toward financial markets. I do a lot of risk management work related to financial institutions and their response to risks in financial markets, but I think that all of the concepts I am going to discuss are applicable to a wide array of issues associated with risk.

I want to start off by defining “risk.” Several of the Symposium contributors have provided definitions of risk. Many of them made a point of relating risk and opportunity. Phillip Howard said risk is the flip side of opportunity. This definition is very consistent with the way risk is viewed in the financial world. The link between risk and reward is a cornerstone of the modeling of financial markets. If taking risk provides the opportunity for reward, it is also important to ask if the fear of accepting risk can cause missed opportunities. This is a central question of the conference today, whether society is becoming risk averse and if that aversion is stifling innovation and therefore economic growth. This implies that individuals in society are sometimes afraid of accepting risk because the potential downside associated with the risk outweighs the potential reward.

Economists think of risk aversion a little differently than most. We do not think of risk aversion as necessarily a fear of risk. By doing so, it ignores the other side of the coin: opportunity. Risk aversion is usually modeled as taking the least risk alternative among those with equal reward. In other words, individuals will accept extra risk as long as there is enough expected reward to compensate for the extra risk. The key to that idea is

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* Associate Professor of Finance, College of Business and Public Administration, Drake University.
expected return—the reward that is expected will likely not actually be the reward actually received. When economists model a financial market, our idea of risk aversion usually relates around questions such as, “Do I expect to get enough compensation to compensate for the extra risk?” If the answer is no, then you are risk averse, but only in the sense that you were not rewarded for accepting the extra risk, that is a different idea than just the straightforward avoidance of risk.

An easy illustration of this is to think about two stocks with an equal return. One is a technology firm with a very uncertain future, and the other is a utility that has been in business for many decades. Why take on the risk of the tech firm if you do not expect to get a higher reward?

The reason I bring that up is that expected return can create a big problem in modeling all areas of risk. Finding a way to handle uncertainty and then relating it to the amount of extra reward necessary to compensate for the risk is a key problem in establishing any formal model of risk. When we think about defining risk, risk and opportunity are tied—but I am going to give you a slightly different and even broader definition. We are going to say risk is something that we do not know with certainty. It is an outcome about which we cannot be certain. How do we model that? Well, that is going to be really difficult because it is so broad.

The big question then becomes, can we develop a probability estimate that accurately portrays the level of uncertainty? If we have a probability estimate and the possible rewards associated with the chance of different outcomes, the challenge is making decisions based upon the estimate that acknowledge the limitations of the mathematical model. Can we say we know—or we do not know with certainty, but we think it is a fifty percent chance or an eighty percent chance, and what does that number mean? That is a really difficult question, and I am going to try to give you a flavor of modeling that idea today—why the models fail or how sometimes they are perceived to fail. I should not say they always fail because they definitely do not. The biggest problem is an overconfidence on the outcome based upon a poor understanding of the model limitations. After addressing some points on modeling, I will try to relate the limitations back to some of the public policy-type questions that are more in tune with everybody in terms of what has been discussed at this Symposium.

Let us first think about a mathematical issue of probability. The whole idea behind this is that we can objectively model risk. We can objectively do this because we have a past history of returns. In other words, our estimate of the future is based upon a foundation of information
from past observations and we are assuming that the future will somehow be similar to the past. Consider the daily return on the two stocks we discussed earlier. There is a past history of the daily returns earned from owning each stock. Assume we have the last ten years of daily returns for both stocks. It is easy to use the past returns to forecast the future return on either stock. We can also combine the stocks into a portfolio and consider how strongly the returns are correlated. We can predict the future return for the portfolio based on the past data. More importantly, we can predict a future distribution of the returns, a range of likely returns each associated with a probability. Assume that we do the math and find out that the expected yearly return on the portfolio is ten percent. This does not mean that the portfolio will provide a ten percent return the next year. It does mean that on average, if we could repeat the same situation over and over, the portfolio will produce a ten percent return.

One of the big things that people have done using that type of modeling is to create a measure called value-at-risk, something that I am sure our Insurance Commissioner is very comfortable thinking about. Value-at-risk takes the distribution that we have found and asks what is the most we might lose in value based on a level of confidence. In other words, we are able to say that we are ninety-five percent confident that the portfolio will not lose more than five percent of its value over the next year. This type of modeling is commonly used to set capital requirements for financial institutions. By setting aside capital that covers a potential loss, the institution is more likely to remain solvent.

For a model like that to work, it makes four very important assumptions. First, it assumes we have the ability to measure all of the inputs and the outcomes. Second, it assumes that the predictability of those inputs stays constant over time. Third, it assumes that that situation is going to be the same going forward as it was in the past, otherwise it is meaningless when used to provide a forecast. Finally, it assumes that we have some ability to either control some of the inputs or at a minimum that we understand what things we can control and which inputs we cannot.

Previously, even if all four assumptions could be satisfied there was a large constraint associated with the ability to gather and quantify the information. However, advances in technology have greatly enhanced our ability to relax this constraint. The ability to compile and process large quantities of information has advanced rapidly during the last twenty or thirty years. This has resulted in a transformation of how risk is modeled, managed, and understood. That leaves us with only the task of addressing each of the assumptions above.
The first three assumptions are all easily illustrated with the stock example. The ability to measure the inputs, predictability of their relationships, and relevance to the future are all easily understood with a long history of stock returns. We can definitely think about how the stocks are correlated over the last five years—when one went up, did the other one go up or down? As for repeatability of the situation, we would like to believe that if we have ten years of data, that the next year, the next day, and the next month is not going to be that much different, but we know things can change. We definitely do not have the ability to control factors in that case. However, we do know the types of factors that will cause a change in the past relationship. For example, if the CEO of one firm is accused of fraud, it is likely that the return on that stock will drop regardless of its past relationship with the other stock.

There is also the ability to select and control the inputs, and then use those inputs to model the risks. If we can measure things well, we can develop a model based on probability that provides insight into the likelihood of a future event. The problem is that most of the risks, especially the ones we talked about in detail today, do not satisfy those assumptions very well. The assumptions are most noticeably violated in two very different ways. Either there is not an ability to measure and monitor the inputs or the model cannot predict the future, especially if the repeatability is not well understood.

When thinking about terrorist attacks, we do not have years of data to support the idea of what is going to be the next target. We can think about whether the terrorists may be more inclined to do a certain act because it has a larger impact, but trying to actually tie some type of probability to it and tie some type of estimate of what the outcome is going to be is much more difficult. That problem makes the measurement part of the risk equation much more complicated.

Repeatability is definitely a problem with those catastrophic risks. The repeatability problem is a huge problem even for the stock example. In the stock example there is a large volume of data and we said we could assume that the future will look like the past. However, this is not as straightforward as it seems. Let me give you an example. For example, imagine you want to add a share of IBM to your portfolio and you say, “Of course I know about IBM, it has been around for a long time.” However, you have to start thinking about questions like, “Should I consider IBM during the 1980s? Should I put that in my model and think about the distribution of returns and how it correlated with the rest of the economy in the 1980s?” Yes, you get several data points with large sample ideas.
That is great. These are large sample ideas. You are supposed to have a large number of observations. But IBM made some really stupid choices in the 1980s. They said, “You know, we do not like this personal computer idea. We have a lot higher margin. We like these mainframe computers. We do not think we need to produce a computer that you put on your desk top.” All of a sudden Dell, Gateway, and other firms came in and stole market share from IBM, and IBM almost failed. Does the management decision there fit the management decision of today, when you think about today’s world and IBM’s position in the marketplace? Probably not, but we are trying to use that data from the past.

Thus, even in the cases when there is a lot of data, modeling problems still exist asking questions such as, “How frequent should that data be?” “Does the daily movement in the stock tell us anything about the management decisions and their valuation and the economic reactions, or should it be a monthly measure?”

The other thing I want you to think about is that the model is based off of a mean variance expected outcome idea. Yesterday, I was talking to a friend of mine who is a tax attorney, and he told me that he had a great economist joke. Three economists go hunting. They see a deer, and the first one takes a shot and misses it five yards to the left. The second one takes a shot and misses it five yards to the right. The third one jumps up and says, “We hit it. We got the deer.” That is the problem with probability modeling.

The mean outcome, that the shot hit exactly in the middle of the spread of outcomes and killed the deer, does not actually happen. It is the average outcome, or the expected outcome, meaning that if the data is repeated over and over, on average the expected outcome occurs. In other words, if the same conditions are repeated a large number of times, we can predict the average outcome. We also know how likely it is that outcomes far from the average will take place. This is the problem—any of those one shots can be way off to the left or the right. We often assume that the mean will occur and forget about the chance of the outcome far from the mean. Even worse, we often underestimate the true frequency of an event occurring. Consider the value at risk example. Assume that we know there is a ninety-five percent chance the value of the portfolio will not decrease by more than five percent over the next day. Assuming 250 trading days a year, this implies that approximately twelve days a year, or one day a month, the portfolio would lose more than five percent of its value. A loss of five percent or greater once a month sounds riskier than a ninety-five percent chance of not losing more than five percent. The less
probable events in the tail of the distribution are those events that represent catastrophic events. These events are often the ones that make people question, “Why did our model not predict this event?” It was there in the model. We just said it was not going to happen very often. It is based off the idea that something is going to be repeated a few thousand times, but that is not what the real world does. So, our model does not match very well sometimes when you measure the risk.

The question then becomes, when you think about a management idea, do those models give us the right question? Are we asking the right question? They are saying we have a chance of a loss. We have a ninety-five percent chance it does not hit some type of limit. Maybe the big question should be: what happens if we are in that five percent tail? What happens if we do not fall into the expected outcome range?

Prospect theory tries to answer those questions. It involves thinking about the downside of risk, and it is not a question of whether we are below that ninety-five percent level; it is if we are below, how far below are we?

I will give you a couple of examples of prospect theory. Let us say you are crossing the street as you walk out today, and you are gauging the cars, looking back and forth trying to decide whether to cross. You were a little late getting to the light and you see some cars coming; maybe they will stop, maybe they will not. You can be pretty sure you are going to cross the street, but if the car runs the light and hits you and you get killed, it is likely that your decisionmaking process was dominated by the thought that you were ninety-five percent sure that you were going to cross the street.

Let us consider some of the examples from the other Symposium participants. We think about the large settlements that people were discussing, or a product liability case that resulted in a large settlement. That is a downside risk type of approach. We are reacting to an outcome that had a very large negative connotation associated with it. That is much different than our mean idea of the distribution, thinking about what the risk is going to be in the middle of the distribution.

That raises several interesting questions regarding how we manage risk. Should we ask the question “what is the chance of a bad outcome?”, or should we ask the question “what happens in the worst case if the bad outcome occurred?”

I will give you another example. I co-authored a paper awhile back in
which we looked at retirement planning.\footnote{Thomas Root & Donald Lien, Allocating Assets in Retirement Savings to Avoid Downside Risk, MANAGERIAL FIN., Aug. 2005, at 18.} We took the portfolio of a risky asset, looking at stocks, and a safer asset—something like a government bond—and said, how much money should be put in each type of asset for retirement? The traditional model looks to achieve the highest expected rate of return. In other words, we are going to think about that mean return and the possible outcomes.

The problem is if a married couple planning for retirement thinks they need one million dollars in the bank and something happens in the market causing their saved funds to drop to $400,000, then suddenly they are in trouble. They may have to move, maybe sell their house, they no longer have the income they thought they would have, and there is a huge emotional impact of not meeting the original goal.

On the other hand, there is the idea if I missed it by a little bit to the left or if I miss it by a little bit to the right that the impact is the same. All of the old probability theory, all of the beginning probability theory, and all of those things that most of our risk modeling is based on says that a five percent loss is the same as a five percent gain, and we respond the same to it. Psychologically we know that is not the case. The pain associated with the five percent loss is often given greater significance than the joy associated with the five percent gain. If we do not account for that in our modeling and account for that in our risk management, it will create a huge problem for us in terms of error arising in our risk management procedures.

In our paper we modeled the portfolio. We looked at a thirty-year window, rolled over the portfolio and inserted all of the possible portfolio combinations. The result we came out with was a really interesting one. The least risky outcome—minimizing the downside risk and eliminating not achieving your retirement income goal—was putting all of the money in the riskiest asset.

The least risky outcome was owning the riskiest asset because that had the longest and most consistent high return over the period of time. For example, investing fifty percent in the bond and fifty percent in the stock, you have approximately a sixty to seventy percent chance of not reaching your retirement income assuming thirty year holding periods each month rolling forward, starting with the 1920 to 1950 investment and carried it through to the year 2000. That is a pretty big difference in
maximizing retirement savings, compared to trying to maximize yearly return.

To tie things back to the public policy discussion, there is the issue of how to decide where government should model, where government should enter, and where government should serve as a risk manager.

The first thing a society ought to think about is the idea of the downside risk. Those things that have a huge emotional attachment are more likely to be misrepresented as the market attempts to price it and are the things that the market is more likely to fail. Those are things like catastrophic events and terrorism. They are not easily addressed with basic insurance products that are based upon spreading risk, but they are issues that have a bad outcome with an emotional tie and cause people to be reactionary.

The other aspects of the behavioral side are two conditions that have led to many new investment strategies in recent years. The first of those conditions is called bounded self-control. It appears in the psychology literature, and bounded self-control says society has a problem of weighing a long-term versus a short-term decision.² The easy example to think about is diet and exercise.

We all know if we do not eat that piece of cake at lunch, it is probably better for our health. We have a better outcome in the long term for our health. But it is really easy to say: “You know, I just need some chocolate today. I can have that sugar to stay awake for the probability talk at the beginning of Symposium this afternoon. I will just start the diet tomorrow.”

You could do that the next day, and the next day, and the next day, and pretty soon you have never done anything to improve your health. The problem is, if we do not feel some type of negative short term emotional attachment, we are less likely to respond to and try to manage that risk.

Now, think about Hurricane Katrina. You have a public policy decisionmaker who says: “There is a small chance of a category five hurricane, this happens once every 100 years and I know the levees are not ready for that. We know that it will be a problem if it occurs, but there is an election soon and I can do this other project with the cash instead of

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addressing the levees. Fixing the levees is not very exciting and it is likely that they will not be a problem in the near future, the next elected officials can deal with it.” The lack of an immediate emotional impact tied to fixing the levees causes the decisionmaker to procrastinate and avoid dealing with the issue. In other words, we discount the short term differently than the long term, and so these unlikely catastrophic events do not get managed. That results in a bad outcome for us as a society.

The second condition is called bounded rationality, which says that some problems get more complex; and our response, as individuals, is to walk away. Retirement planning is a good example of bounded rationality. A 2004 study written for Vanguard asked if more choice among investment funds in a retirement plan impacts participation in the plan. As they increased the number of funds participants had to choose from, participation in the plans dropped. The reason for the decrease is that everyone became overwhelmed by the choices. Everyone looked at the choices and said: “I just cannot really understand this; I do not have time to try to work this out.” They created a nervous emotional attachment and walked away instead of choosing to participate. The levees are again a great example of this. The complexity associated with solving the issues of the weak levees was large and very difficult to handle. It is much easier to address a simple problem that is very visible. That creates a huge problem for risk management. If we have people who are opting out of the system—even if they know about the risk—and and are asked about planning for retirement, most respond with an affirmative response. They are then asked whether they will be part of the system, and most people respond with something to the effect of “No, but I plan to be.”

We heard earlier today this idea of how to think about defined benefit versus defined contribution pension plans. With defined contribution plans, everybody manages their own retirement saving. However this is a very complex problem with a long-term horizon. It is a perfect example of how both bounded rationality and bounded self control limit the ability of individuals to plan adequately. Therefore, individuals are unwilling to participate from the psychological perspective. The human element is important.

It returns to a value judgment. It comes back to considering not only how we measure risk but also how individuals view risk. Ultimately, the way we psychologically view risk plays as large of a role in the success of our models as the mathematical theory they are based upon.

The problem with a lot of our models—and I admit I spent a lot of time thinking about building these models and working on these models—is they do not account for that human element. Quite often because the models do not account for that human element, they start to fail in producing the results we want.

The bottom line of this talk is that we can build models based on objective probability and attempt to deal with all the issues in the probability estimate, but there is an underlying human element that is very difficult to take into account. The key is trying to identify which risks to accept. I do not have the answer for which ones we should accept, which ones the market can cover, and which ones the government can and should address.

The final word I want to give you is a short story that I think really sums up how we should view risk. I heard the chief risk officer of one of the large insurance companies based in town the other day give a presentation to some of the managers of the firm. The comment she made to the group was, “We are not risk adverse, we are just risk aware.” I thought that simple statement summed up measuring and managing risk very well. To be able to manage risk we have to be able to understand all of the issues with any attempts we make to measure it. We also have to be aware of the risks posed by potential flaws in the model. We have to worry about overconfidence in our ability to model risk and include a very critical assessment of our models, especially how they deal with the human factor. Only then can we decide what risks should be accepted and which should not.