DFA – Dynamic Financial Analysis

Overview

Dynamic Financial Analysis ('DFA') is a systematic approach based on large-scale computer simulations for the integrated financial modeling of nonlife insurance and reinsurance companies aimed at assessing the risks and the benefits associated with strategic decisions.

The most important characteristic of DFA is that it takes an integrated, holistic point of view, contrary to classic financial or actuarial analysis in which different aspects of one company were considered in isolation from each other. Specifically, DFA models the reactions of the company in response to a large number of interrelated risk factors including both **underwriting risks** – usually from several different lines of business, as well as **asset risks**. In order to account for the long time horizons that are typical in insurance and reinsurance, DFA allows dynamic projections to be made for several time periods into the future, where one time period is usually one year, sometimes also one quarter. DFA models normally reflect the full financial structure of the modeled company, including the impact of accounting and tax structures. Thus, DFA allows projections to be made for the **balance sheet** and for the **profit-and-loss account** ('P&L') of the company. Technically, DFA is a platform using various models and techniques from finance and actuarial science by integrating them into one multivariate dynamic simulation model. Given the complexity and the long time horizons of such a model, it is not anymore possible to make analytical evaluations. Therefore, DFA is based on stochastic simulation (also called **Monte Carlo imulation**), where large numbers of random scenarios are generated, the reaction of the company on each one of the scenarios is evaluated, and the resulting outcomes are then analyzed statistically. The section 'The Elements of DFA' gives an in-depth description of the different elements required for a DFA.

With this setup, DFA provides insights into the sources of value creation or destruction in the company and into the impact of external risk factors as well as internal strategic decisions on the bottom line of the company, that is, on its financial statements. The most important virtue of DFA is that it allows an insight into various kinds of dependencies that affect the company, and that would be hard to grasp without the holistic approach of DFA. Thus, DFA is a tool for integrated enterprise risk management and strategic decision support. More popularly speaking, DFA is a kind of flight simulator for decision makers of insurance and reinsurance companies that allows them to investigate the potential impact of their decisions while still being on safe grounds. Specifically, DFA addresses issues such as **capital management**, **investment strategies**, **reinsurance strategies**, and strategic **asset–liability management**. The section 'The Value Proposition of DFA' describes the problem space that gave rise to the genesis of DFA, and the section 'DFA Use Cases' provides more information on the uses of DFA.

The term DFA is mainly used in **nonlife insurance**. In life insurance, techniques of this kind are usually termed **Asset Liability Management ('ALM')**, although they are used for a wider range of applications – including the ones stated above. Similar methods are also used in banking, where they are often referred to as 'Balance Sheet Management'.

DFA grew out of practical needs, rather than academic research in the late 1990s. The main driving force behind the genesis and development of DFA was, and still is, the related research committee of the **Casualty Actuarial Society (CAS)**. Their website (http://www.casact.org/research/dfa/index.html), provides a variety of background materials on the topic, in particular, a comprehensive and easy-to-read handbook [9] describing the value proposition and the basic concepts of DFA. A fully worked-out didactic example of a DFA with emphasis on the underlying quantitative problems is given in [18], whereas [21] describes the development and implementation of a large-scale DFA decision support system for a company. In [8], the authors describe comprehensively all modeling elements needed for setting up a DFA system, with main emphasis on the underwriting side; complementary information can be found in [3].

The Value Proposition of DFA

The aim of this section is to describe the developments in the insurance and reinsurance market that gave rise to the genesis of DFA. For a long time – up until the 1980s or 1990s, depending on the country – insurance business used to be a fairly quiet area, characterized by little strategic flexibility and innovation. Regulations heavily constrained the insurers in the types of business they could assume, and also in the way they had to do the business. Relatively simple products were predominant, each one addressing a specific type of risk, and underwriting and investment were separated, within the (nonlife) **insurance companies** themselves and also in the products they offered to their clients. In this rather static environment, there was no particular need for sophisticated analytics: actuarial analysis was carried out on the underwriting side – without linkage to the investment side of the company, which was analyzed separately. **Reinsurance** as the only means of managing underwriting risks was acquired locally per line of business, whereas there were separate **hedging** activities for financial risks. Basically, quantitative analysis amounted to modeling a group of isolated silos, without taking a holistic view.

However, insurance business is no longer a quiet area. Regulations were loosened and gave more strategic flexibility to the insurers, leading to new types of complicated products and to a fierce competition in the market. The traditional separation between banking and insurance business became increasingly blurred, and many companies developed into integrated financial services providers through mergers and acquisitions. Moreover, the risk landscape was also changing because of demographic, social, and political changes, and because of new types of insured risks or changes in the characteristics of already-insured risks (e.g. liability). The boom in the financial markets in the late 1990s also affected the insurers. On the one hand, it opened up opportunities on the investment side. On the other hand, insurers themselves faced shareholders who became more attentive and demanding. Achieving a sufficient return on the capital provided by the investors was suddenly of paramount importance in order to avoid a capital drain into more profitable market segments. A detailed account on these developments, including case studies on some of their victims, can be found in [5].

As a consequence of these developments, insurers have to select their strategies in such a way that they have a favorable impact on the bottom line of the company, and not only relative to some isolated aspect of the business. **Diversification** opportunities and offsetting effects between different lines of business or between underwriting risks and financial risks have to be exploited. This is the domain of a new discipline in finance, namely, Integrated or Enterprise Risk Management, see [6]. Clearly, this new approach to **risk management** and decision making calls for corresponding tools and methods that permit an integrated and holistic quantitative analysis of the company, relative to all relevant risk factors and their interrelations. In nonlife insurance, the term 'DFA' was coined for tools and methods that emerged in response to these new requirements. On the technical level, **Monte Carlo simulation** was selected because it is basically the only means that allows one to deal with the long time horizons present in insurance, and with the combination of models for a large number of interacting risk factors.

The Elements of DFA

This section provides a description of the methods and tools that are necessary for carrying out DFA. The structure referred to here is generic in that it does not describe specifically one of the DFA tools available in the market, but it identifies all those elements that are typical for any DFA. DFA is a software-intensive activity. It relies on complex software tools and extensive computing power. However, we should not reduce DFA to the pure software aspects. Full-fledged and operational DFA is a combination of software, methods, concepts, processes, and skills. Skilled people are the most critical ingredient to carry out the analysis. In Figure 1, we show a schematic structure of a generic DFA system with its typical components and relations.

The *scenario generator* comprises stochastic models for the risk factors affecting the company. **Risk factors** typically include economic risks (e.g. inflation), liability risks (e.g. motor liability claims), asset risks (e.g. stock market returns), and business risks (e.g. underwriting cycles). The output of the scenario generator is a large number of Monte Carlo scenarios for the joint behavior of all modeled risk factors over the full time range of the study, representing possible

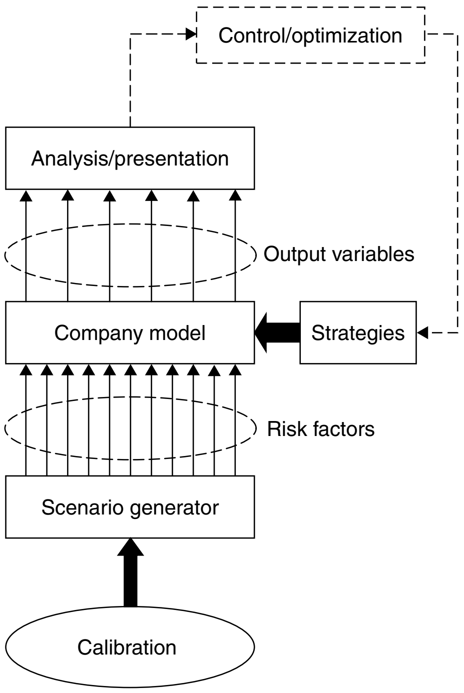

Figure 1 Schematic overview of the elements of DFA

future 'states-of-nature' (where 'nature' is meant in a wide sense). *Calibration* means the process of finding suitable parameters for the models to produce sensible scenarios; it is an integral part of any DFA. If the Monte Carlo scenarios were replaced by a small set of constructed scenarios, then the DFA study would be equivalent to classical scenario testing of business plans.

Each one of the scenarios is then fed into the *company model* or **model office** that models the reaction of the company on the behavior of the risk factors as suggested by the scenarios. The company model reflects the internal financial and operating structure of the company, including features like the consolidation of the various lines of business, the effects of reinsurance contracts on the risk assumed, or the structure of the investment portfolio of the company, not neglecting features like accounting and taxation.

Each company model comprises a number of parameters that are under the control of management, for example, investment portfolio weights or reinsurance retentions. A set of values for these parameters corresponds to a strategy, and DFA is a means for comparing the effectiveness of different strategies under the projected future course of events. The output of a DFA study consists of the results of the application of the company model, parameterized with a strategy, on each of the generated scenarios. So, each risk scenario fed into the company model is mapped onto one result scenario that can also be multivariate, going up to full pro forma balance sheets.

Given the Monte Carlo setup, there is a large number of output values, so that sophisticated *analysis and presentation* facilities become necessary for extracting information from the output: these can consist of statistical analysis (e.g. empirical moment and quantile computations), graphical methods (e.g. empirical distributions), or also drill-down analysis, in which input scenarios that gave rise to particularly bad results are identified and studied. The results can then be used to readjust the strategy for the *optimization* of the target values of the company. The rest of this section considers the different elements and related problems in somewhat more detail.

Scenario Generator and Calibration

Given the holistic point of view of DFA, the scenario generator has to contain stochastic models for a large

Economic	Claims	Investment	Business
Per economy:	Per LOB:	Government bonds	(Underwriting cycles)
−Inflation	−Attritional losses	Stocks	(Reinsurance cycles)
−Interest rates	−Large losses	Real estate	(Operational risks)
	−Loss development		(etc.)
(Exchange rates)	Across LOBs:	(Corporate bonds)	
(Credit spreads)	−CAT losses	(Asset-backed securities)	
(GDP)		(Index-linked securities)	
(Wage levels)	(Reserve uncertainty)	(etc.)	
(etc.)	(etc.)		

number of risk factors, belonging to different groups; the table below gives an overview of risk factors typically included (in parentheses: optional variables in more sophisticated systems).

The scenario generator has to satisfy a number of particular requirements: First of all, it does not only have to produce scenarios for each individual risk factor, but must also allow, specify, and account for **dependencies** between the risk factors (contemporaneous dependencies) and dependencies over time (intertemporal dependencies). Neglecting these dependencies means underestimating the risks since the model would suggest diversification opportunities where actually none are present. Moreover, the scenarios should not only reproduce the 'usual' behavior of the risk factors, but they should also sufficiently account for their extreme individual and joint outcomes.

For individual risk factors, many possible models from actuarial science, finance, and economics are available and can be reused for DFA scenario generation. For underwriting risks, the models used for pricing and reserving can be reused relatively directly, see for example [8] for a comprehensive survey. Attritional losses are usually modeled through **loss ratios** per line of business, whereas large losses are usually modeled through frequency–severity setups, mainly in order to be able to reflect properly the impact of **nonproportional reinsurance**. Catastrophe (CAT) modeling is special in that one CAT event usually affects several lines of business. **CAT modeling** can also be done through **stochastic models** (see [10]), but – for the perils covered by them – it is also fairly commonplace to rely on scenario output from special CAT models such as CATrader© (see www.air-boston.com), RiskLink© (see www.rms.com), or EQEcat© (see www.eqecat.com). As DFA is used for simulating business several years ahead, it is important to model not only the incurred losses but also the development of the losses over time – particularly their payout patterns, given the cash flow–driven nature of the company models. Standard actuarial loss reserving techniques are normally used for this task, see [18] for a fully worked-out example. Reference [23] provides full details on modeling loss reserves, including stochastic payout patterns that allow the incorporation of specific reserving uncertainty that is not covered by the classical techniques.

Among the economic and financial risk factors, the most important ones are the **interest rates**. There exists a large number of possible models from the realm of finance for modeling single interest rates or – preferably – full yield curves, be it riskless ones or risky ones; and the same is true for models of **inflation**, credit spreads, or equities. Comprehensive references on these topics include [3, 17]. However, some care must be taken: most of these models were developed with tasks other than simulation in mind, namely, the valuation of **derivatives**. Thus, the structure of these models is often driven by mathematical convenience (easy valuation formulae for derivatives), which often goes at the expense of good statistical properties. The same is true for many econometric models (e.g. for inflation), which tend to be optimized for explaining the 'usual' behavior of the variables while neglecting the more '**extreme**' events. In view of the difficulties caused by the composition of existing models for economic variables and invested assets, efforts have been made to develop integrated economic and asset scenario generators that respond to the particular requirements of DFA in terms of statistical behavior, dependencies, and long-term stability. The basics for such economic models and their integration, along with the **Wilkie model** as the most classical example, are described in [3]. [20] provides a survey and comparison of several integrated economic models (including the ones by Wilkie, Cairns, and Smith) and pointers to further references. Besides these publicized models, there are also several proprietary models by vendors of actuarial and financial software (e.g. B&W Deloitte (see www.timbuk1.co.uk), Barrie & Hibbert (see www.barrhibb.com), SS&C (see www.ssctech.com), or Tillinghast (see www.towers.com).

Besides the **underwriting risks** and the basic economic risk factors as inflation, (government) interest rates, and equities, sophisticated DFA scenario generators may contain models for various further risk factors. In international setups, foreign exchange rates have to be incorporated, and an additional challenge is to let the model also reflect the international dependencies. Additional risk factors for one economy may include Gross Domestic Product (GDP) or specific relevant types of inflation as, for example, wage or medical inflation. Increasingly important are also models for **credit defaults and credit spreads** – that must, of course, properly reflect the dependencies on other economic variables. This, subsequently, allows one to model investments like asset-backed securities and corporate bonds that are extremely important for insurers, see [3]. The modeling of operational risks (see [6], which also provides a very general overview and classification of all risks affecting financial companies), which are a current area of concern in banking regulation, is not yet very widespread in DFA. An important problem specific to insurance and reinsurance is the presence of underwriting cycles ('hard' and 'soft' markets), which have a nonnegligible business impact on the long time horizons considered by DFA. These cycles and their origins and dependencies are not very well understood and are very difficult to model; see [12] for a survey of the current state of knowledge.

The real challenge of DFA scenario generation lies in the composition of the component models into an integrated model, that is, in the modeling of dependencies across as many outcomes as possible. These dependencies are ubiquitous in the risk factors affecting an insurance company, think, for example, of the well-known fact that car accidents tend to increase with increasing GDP. Moreover, many of those dependencies are nonlinear in nature, for example, because of market elasticities. A particular challenge in this context is the adequate assessment of the impact of extreme events, when the historically observable dependency becomes much stronger and risk factors appear much more interrelated (the so-called tail dependency). Different approaches for dependency modeling are pursued, namely:

- Deterministic modeling by postulating functional relations between various risk factors, for example, mixture models or **regression-type models**, see [8, 17].
- Statistical modeling of dependencies, with linear correlation being the most popular concept. However, linear correlation has some serious limitations when extreme values are important; see [11] for a related study, possible modeling approaches and pointers to further readings.

An important aspect of the scenario generator is its calibration, that is, the attribution of values to the parameters of the stochastic model. A particular challenge in this context is that there are usually only few data points for estimating and determining a large number of parameters in a high-dimensional space. This can obviously result in substantial **parameter uncertainty**. Parsimony and transparency are, therefore, crucial requirements for models being used in DFA scenario generation. In any case, calibration, which also includes backtesting of the calibrated model, must be an integral part of any DFA study. Even though most DFA practitioners do not have to deal with it explicitly, as they rely on commercially available DFA software packages or components, it should not be forgotten that, at the end, generating Monte Carlo scenarios for a large number of dependent risk factors over several time periods also poses some non-trivial numerical problems. The most elementary example is to have a random number generator that is able to produce thousands, if not millions, of independent and identically distributed random variables (indeed a nontrivial issue in view of the sometimes poor performance of some popular random number generators). The technicalities of **Monte Carlo methods** are comprehensively described in [13].

Moreover, it is fundamentally difficult to make judgments on the plausibility of scenarios for the expanded time horizons often present in DFA studies. Fitting a stochastic model either to historical or current market data implies the assumption that history or current expectations are a reliable prediction for the future. While this may be true for short time horizons, it is definitely questionable for time horizons as long as 5 to 20 years, as they are quite commonplace in insurance. There are regime switches or other hitherto unexperienced events that are not reflected by historical data or current market expectations. Past examples include asbestos liabilities or the events of September 11, 2001. An interesting case study on the issue is [4], whereas [22] explores in very general, the limitations of risk management based on stochastic models and argues that the latter must be complemented with some judgmental crisis scenarios.

Company and Strategy Modeling

Whereas the scenarios describe possible future courses of events in the world surrounding the modeled company, the company model itself reflects the reaction of the company in response to the scenario. The task of the company model is to consolidate the different inputs into the company, that is, to reflect its internal operating structure, including the insurance activities, the **investment activities**, and also the impact of **reinsurance**.

Company models can be relatively simple, as the ones in [8, 18], which basically consolidate in a purely technical way the outcomes of the various risks. However, the goal of DFA is to make projections for the bottom line of the company, that is, its financial statements. Therefore, practical DFA company models tend to be highly complex. In particular, they also incorporate the effects of **regulation**, accounting, and taxation, since these issues have an important impact on the behavior and the financial results of insurance companies. However, these latter issues are extremely hard to model in a formal way, so that there is quite some model uncertainty emanating from the company model. Examples of detailed models for US property–casualty insurers are described in [10, 16]. In general, even relatively simple company models are already so complicated that they do not anymore represent mathematically tractable mappings of the input variables on the output variables, which precludes the use of formal optimization techniques as, for example, dynamic programming. This distinguishes practical DFA models from technically more sophisticated dynamic optimization models coming from the realm of **operations research**, see [19]. Figure 2 shows an extract of a practical DFA company model, combining components that provide the scenario input, components that model the aggregation and consolidation of the different losses, components that model the in-force reinsurance programs, and components that aggregate the results into the company's overall results. It should be borne in mind that each component contains, moreover, a number of parameters (e.g. reinsurance retentions and limits). The partial model shown in Figure 2 represents just one line of business of a company; the full model would then contain several other lines of business, plus the entire investment side of the company, plus the top level structure consolidating everything into the balance sheet. This gives us a good idea of the actual complexity of real-world DFA models.

Company models used in DFA are usually very cash flow–oriented, that is, they try to imitate the cash flows of the company, or, more specifically, the technical, and financial accounting structures. Alternatively, it would be imaginable to structure a company model along the lines of economic value creation. The problem with this approach is, however, that this issue is not very well understood in insurance; see [14] for a survey of the current state of the knowledge.

The modeling of the strategies (i.e. the parameters of the company model that are under the control of management) is usually done in a nonadaptive way, that is, as deterministic values over time. However, a DFA study usually involves several time periods of substantial length (one year, say), and it is not realistic to assume that management will not adapt its strategy if the underlying risk factors develop dramatically in a particular scenario.

For the reasons stated, the plausibility and accuracy of DFA outputs on balance sheet level is often doubted, and the true benefit of a DFA study is rather seen in the results of the analytical efforts for setting up a comprehensive model of the company and the relevant risk factors.

Analysis and Presentation

The output of a DFA simulation consists of a large number of random replicates (= possible results) for several output variables and for several future time points (see Figure 3 to get an idea), which implies the need for sophisticated analysis and presentation techniques in order to be able to draw sensible conclusions from the results.

The first step in the analysis procedure consists of selecting a number of sensible output variables, where the term 'sensible' is always relative to the goals of the study. Typical examples include earnings before or after interest and tax, or the level of shareholders' equity. Besides such economic target variables, it is sensible to compute at the same time, certain regulatory values, for example, the IRIS ratios in North America, see [10], by which one can assess whether a strategy is consistent with in force regulations. More information on the selection of target variables is given in [9].

Once the target variables are selected, there still remains the task of analyzing the large number of random replicates: suppose that Y is one of the target variables, for example, shareholders' equity, then, the DFA simulation provides us with random replicates $y_1, \ldots, y_N$, where N is typically high.

The most common approach is to use statistical analysis techniques. The most general one is to analyze the full **empirical distribution** of the variable,

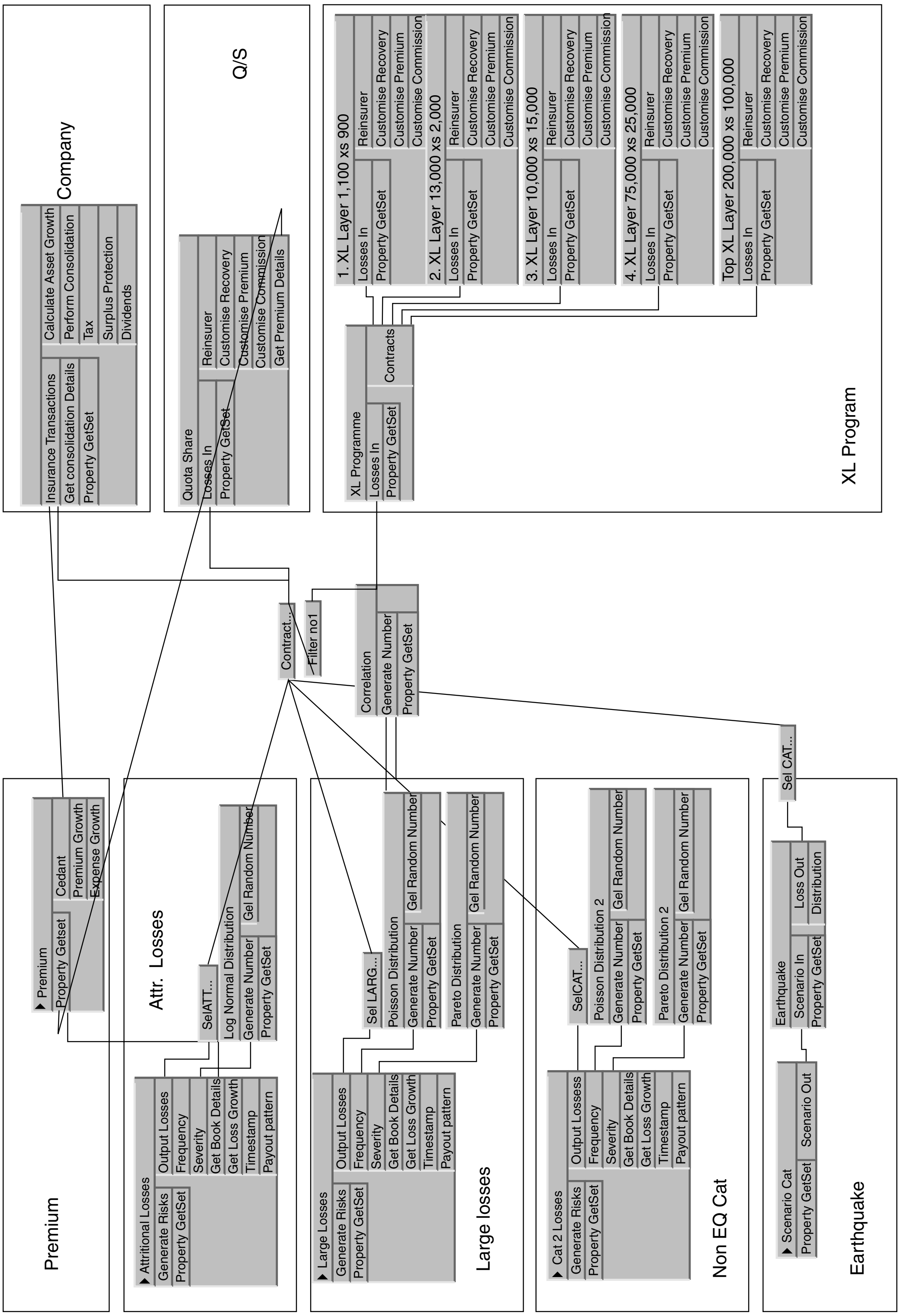

Figure 2 Extract from a DFA company model

	1Q2003	4Q2002	3Q2002	2Q2002	1Q2002
Earned premium income	1'061.4	1'713.3	1653.2	787.0	694.4
Losses incurred	–881.4	–1415.3	–1277.6	–647.9	–819.4
Total U/W expenses					
Underwriting results					
Invested assets					
Total other assets					
Technical reserves					
Total other liabilities					
Liabilities					
Total equity & liabilities					
ROE					
Solvency ratio					
Reserve ratio					
Asset leverage					

t_0

	1Q2004	4Q2003	3Q2003	2Q2003	1Q2003
Earned premium income	1'125.1	1'816.1	1'752.4	834.2	730.8
Losses incurred	–934.3	–1'500.2	–1'354.3	–686.8	–868.6
Total U/W expenses					
Underwriting results					
Invested assets					
Total other assets					
Technical reserves					
Total other liabilities					
Liabilities					
Total equity & liabilities					
ROE					
Solvency ratio					
Reserve ratio					
Asset leverage					

$t_0 + \Delta t$

	1Q2005	4Q2004	3Q2004	2Q2004	1Q2004
Earned premium income	1'192.6	1'925.1	1'857.5	884.3	774.6
Losses incurred	–990.3	–1'590.2	–1'435.5	–728.0	–920.7
Total U/W expenses					
Underwriting results					
Invested assets					
Total other assets					
Technical reserves					
Total other liabilities					
Liabilities					
Total equity & liabilities					
ROE					
Solvency ratio					
Reserve ratio					
Asset leverage					

$t_0 + 2\Delta t$

	1Q2006	4Q2005	3Q2005	2Q2005	1Q2005
Earned premium income	1'264.1	2'040.6	1'969.0	937.3	821.1
Losses incurred	–1'049.8	–1'685.6	–1'521.6	–771.7	–975.9
Total U/W expenses	–222.2	–310.1	–295.0	–623.9	–100.3
Underwriting results	–7.9	44.8	152.3	–458.2	–255.1
Invested assets	8'249.2	6'951.5	6,475.1	6'248.8	6'134.6
Total other assets	2'714.2	2'788.8	1'825.9	1'920.5	2'295.9
Technical reserves	6'899.8	6'615.1	6'558.7	6'336.7	6'236.3
Total other liabilities	2'277.2	937.0	1'322.1	832.3	882.1
Liabilities	9'177.0	9'403.9	7'880.8	7'169.0	7'118.3
Total equity & liabilities	1'786.4	336.3	420.2	1'000.3	1'312.1
ROE	0.2	0.2	0.2	0.1	0.1
Solvency ratio	1.2	1.0	1.1	1.0	1.0
Reserve ratio	3.3	3.9	3.4	3.4	4.0
Asset leverage	4.2	4.4	3.9	4.0	3.6

$t_0 + 3\Delta t$

$\Delta t = 1$ year

Figure 3 Extract of pro forma projected balance sheets

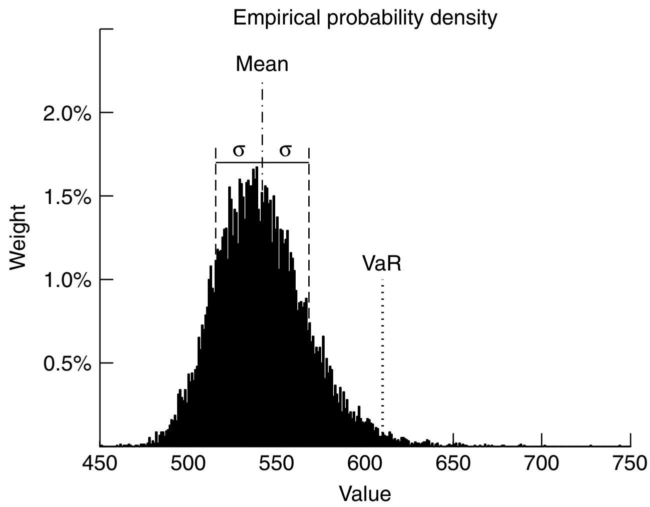

Figure 4 A P&L distribution and some measures of risk and reward

that is, to compute and plot

$$\hat{F}_Y(y) = \frac{1}{N}\sum_{k=1}^{N} 1(y_k \leq y). \qquad (1)$$

Figure 4 shows an example, together with some of the measures discussed below. For comparisons and for taking decisions, it is more desirable to characterize the result distribution by some particular numbers, that is, by values characterizing the average level and the variability (i.e. the riskiness) of the variable. For the average value, one can compute the empirical mean, that is,

$$\hat{\mu}(Y) = \frac{1}{N}\sum_{k=1}^{N} y_k. \qquad (2)$$

For **risk measures**, the choice is less obvious. The most classical measure is the empirical standard deviation, that is,

$$\hat{\sigma}(Y) = \left(\frac{1}{N-1}\sum_{k=1}^{N}(y_k - \hat{\mu})^2\right)^{1/2}. \qquad (3)$$

The standard deviation is a double-sided risk measure, that is, it takes into account deviations to the upside as well as to the downside equally. In **risk management**, however, one is more interested in the potential downside of the target variable. A very popular measure for downside risk is the **Value-at-Risk (VaR)**, which is simply the p-quantile for the distribution of Y for some probability $0 < p < 1$. It is easily computed as

$$\widehat{\mathrm{VaR}}_p(Y) = \min\left\{y_{(k)} : \frac{k}{N} > p\right\}. \qquad (4)$$

where $y_{(k)}$ is the kth order statistic of $y_1, \ldots, y_N$. Popular risk measures from the realm of actuarial science include, for example, expected policyholder deficit, twisted means or Wang and **Esscher transforms**, see [8, 9] for more details. Another downside risk measure, extending the already introduced VaR, is the TailVaR, defined as

$$\mathrm{TailVaR}_p(Y) = \mathrm{E}(Y|Y \geq \mathrm{VaR}_p(Y)), \qquad (5)$$

which is the expectation of Y, given that Y is beyond the VaR-threshold (Expected Shortfall), and which can be computed very easily by averaging over all replicates beyond VaR. The particular advantage of TailVaR is that – contrary to most other risk measures including VaR and standard deviation – it belongs to the class of *Coherent Risk Measures*; see [1] for full details. In particular, we have that

$$\mathrm{TailVaR}_p(Y + Z) \leq \mathrm{TailVaR}_p(Y) + \mathrm{TailVaR}_p(Z), \qquad (6)$$

that is, diversification benefits are accounted for. This aggregation property is particularly desirable if one analyzes a multiline company, and one wants to put the results of the single lines of business in relation with the overall result. Another popular approach, particularly for reporting to the senior management, is to compute probabilities that the target variables exceed certain thresholds, for example, for bankruptcy; such probabilities are easily computed by

$$\hat{p} = \frac{1}{N}\sum_{k=1}^{N} 1(y_k \geq y_{\text{threshold}}) \qquad (7)$$

In a multiperiod setup, measures of risk and reward are usually computed either for each time period $t_0 + n \cdot \Delta t$ individually, or only for the terminal time T, see Figure 5. An important caveat to be accounted for in this setup is that the target variable may temporally assume values that correspond to a disruption of the ordinary course of business (e.g. ruin or regulatory intervention); see again Figure 5. Such degenerate trajectories have to be accounted for in suitable ways, otherwise the terminal results may no longer be realistic.

By repeating the simulation and computing the target values for several different strategies, one can compare these strategies in terms of their risks and rewards, determine ranges of feasible and attainable results, and finally, select the best among the feasible strategies. Figure 6 shows such a comparison, conceptually very similar to risk–return analysis in classical portfolio theory. It is, however, important to notice that DFA does not normally allow for the use of formal optimization techniques (such as convex

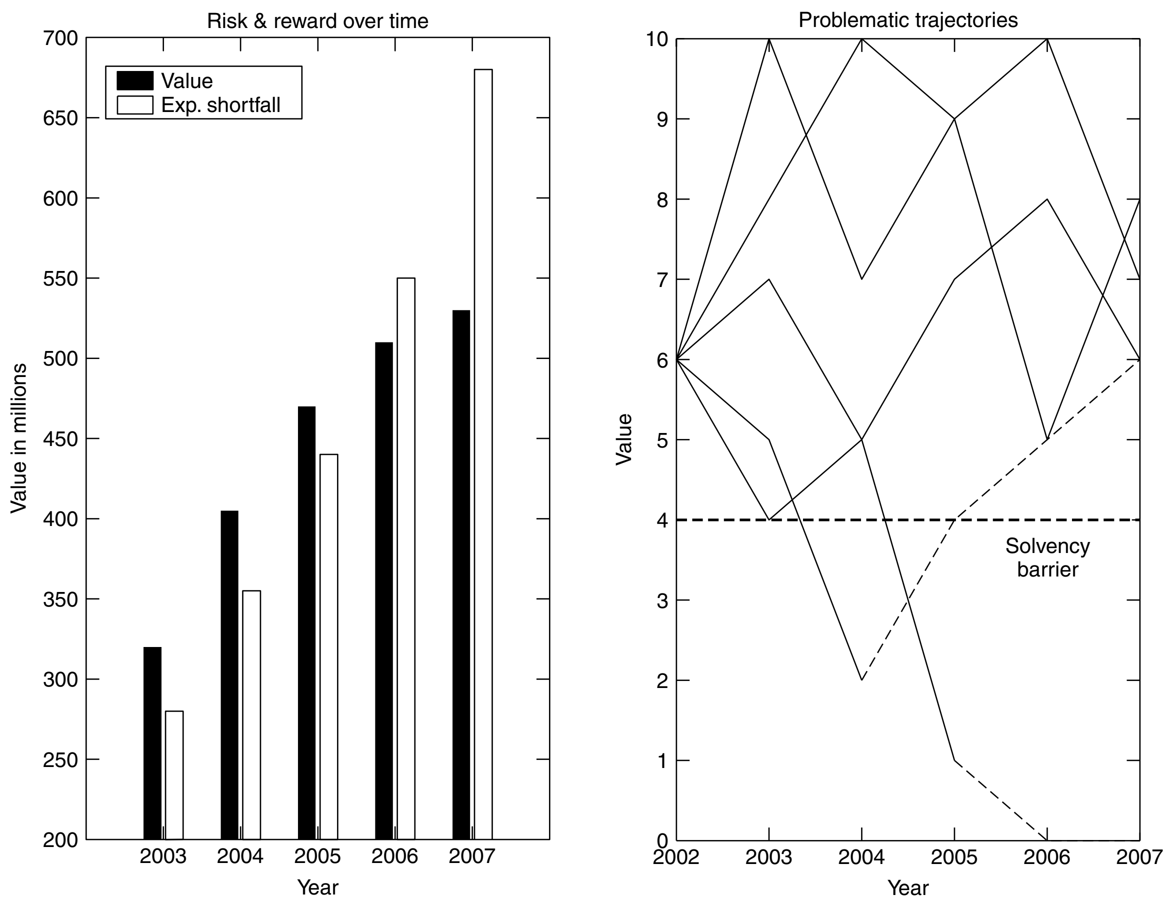

Figure 5 Evolution of expected surplus and expected shortfall over time

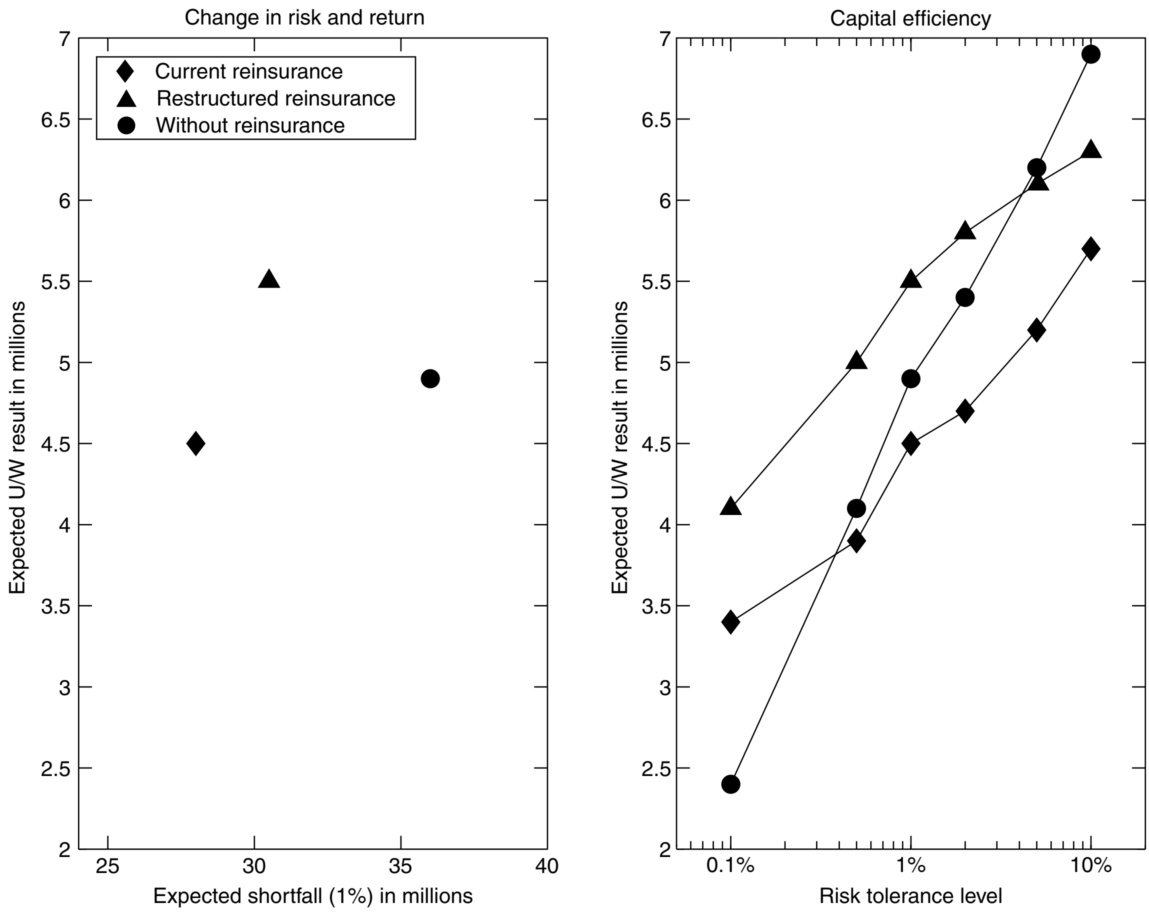

Figure 6 Risk-return-type diagram

optimization), since the structure of the model is too irregular. The optimization rather consists of educated guesses for better strategies and subsequent evaluations thereof by carrying out a new simulation run. Such repeated simulation runs with different strategy settings (or also with different calibrations of the scenario generator) are often used for exploring the sensitivities of the business against strategy changes or against changes in the environment, that is, for exploring relative rather than absolute impacts in order to see what strategic actions do actually have a substantial leverage.

An alternative to this statistical type of analysis is drill-down methods. Drill-down consists of identifying particularly interesting (in whatever sense) output values y_k, to identify the input scenarios x_k that gave rise to them, and then to analyze the characteristics of these input scenarios. This type of analysis requires the storage of massive amounts of data, and doing sensible analysis on the usually high-dimensional input scenarios is not simple either.

More information on analysis and presentation can be found in a related chapter in [9], or, for techniques more closely related to **financial economics**, in [7].

The DFA Marketplace

There are a number of companies in the market that offer software packages or components for DFA, usually in conjunction with related consulting services (recall from the beginning of this section that DFA is not only a software package, but rather a combination of software, processes, and skills). In general, one can distinguish between two types of DFA software packages:

1. Flexible, modular environments that can be adapted relatively quickly to different company structures, and that are mainly used for addressing dedicated problems, usually the structuring of complex reinsurance programs or other deals.
2. Large-scale software systems that model a company in great detail and that are used for internal risk management and strategic planning purposes on a regular basis, usually in close connection with other business systems.

Examples for the first kind of DFA software include Igloo by Paratus Consulting (see www.paratusconsulting.com) and Remetrica II by Benfield Group (see www.benfieldgreig.com). Examples for the second kind of DFA systems include Finesse 2000 by SS&C (see www.ssctech.com), the general insurance version of Prophet by B&W Deloitte (see www.bw-deloitte.com), TAS P/C by Tillinghast (see www.towers.com) or DFA by DFA Capital Management Inc (see www.dfa.com). Dynamo by MHL Consulting (see www.mhlconsult.com) is a freeware DFA software based on Excel. It belongs to the second type of DFA software and is actually the practical implementation of [10]. An example of a DFA system for rating agency purposes is [2]. Moreover, some companies have proprietary DFA systems that they offer to customers in conjunction with their consulting and brokerage services, examples including Guy Carpenter (see www.guycarp.com) or AON (see www.aon.com).

DFA Use Cases

In general, DFA is used to determine how an insurer might fare under a range of future possible environment conditions and strategies. Here, environment conditions are topics that are not under the control of management, whereas strategies are topics that are under the control of management. Typical strategy elements whose impact is explored by DFA studies include the following:

Business mix: relative and absolute volumes in the different lines of business, premium, and commission level, and so on.

Reinsurance: reinsurance structures per line of business and on the entire account, including contract types, dependencies between contracts, parameters (quota, deductibles, limits, reinstatements, etc.), and cost of reinsurance.

Asset allocation: normally only on a strategic level; allocation of the company's assets to the different investment asset classes, overall or per currency; portfolio rebalancing strategies.

Capital: level and structure of the company's capital; equity and debt of all kinds, including dividend payments for equity, coupon schedules, and values, redemption and embedded options for debt, allocation of capital to lines of business, return on capital.

The environment conditions that DFA can investigate include all those that the scenario generator can model; see section 'The Elements of DFA'. The generators are usually calibrated to best estimates for the future behavior of the risk factors, but one can also use conscious miscalibrations in order to investigate the company's sensitivity to unforeseen changes. More specifically, the analysis capabilities of DFA include the following:

Profitability: Profitability can be analyzed on a cash-flow basis or on a return-on-capital basis. DFA allows profitability to be measured per line of business or for the entire company.

Solvency: DFA allows the solvency and the liquidity of the company or parts of it to be measured, be it on an economic or on a statutory basis. DFA can serve as an early warning tool for future solvency and liquidity gaps.

Compliance: A DFA company model can implement regulatory or statutory standards and mechanisms. In this way, the compliance of the company with regulations, or the likelihood of regulatory interventions can be assessed. Besides legal ones, the standards of rating agencies are of increasing importance for insurers.

Sensitivity: One of the most important virtues of DFA is that it allows the exploring of how the company reacts to a change in strategy (or also a change in environment conditions), relative to the situation in which the current strategy pertains also to the future.

Dependency: Probably the most important benefit of DFA is that it allows to discover and analyze dependencies of all kinds that are hard to grasp without a holistic modeling and analysis tool. A very typical application here is to analyze the interplay of assets and liabilities, that is, the strategic **asset liability management** ('ALM').

These analytical capabilities can then be used for a number of specific tasks, either on a permanent basis or for one-time dedicated studies of special issues. If a company has set up a DFA model, it can recalibrate and rerun it on a regular basis, for example, quarterly or yearly, in order to evaluate the in-force strategy and possible improvements to this strategy. In this way, DFA can be an important part of the company's business planning and enterprise risk management setup. On the other hand, DFA studies can also be made on a one-time basis, if strategic decisions of great significance are to be made. Examples for such decisions include mergers and acquisitions, entry in or exit from some business, thorough rebalancing of reinsurance structures or investment portfolios, or capital market transactions. Basically, DFA can be used for assessing any strategic issues that affect the company as a whole. However, the exact purpose of the study has some drawbacks on the required structure, degree of refinement, or time horizon of the DFA study (particularly the company model and the scenario generator).

The main users of DFA are the insurance and reinsurance companies themselves. They normally use DFA models on a permanent basis as a part of their risk management and planning process [21]; describes such a system. DFA systems in this context are usually of substantial complexity, and only a continued use of them justifies the substantial costs and efforts for their construction. Another type of users are consulting companies and brokers who use dedicated – usually less complex – DFA studies for special tasks, for example, the structuring of large and complicated deals. An emerging class of users are regulatory bodies and rating agencies; they normally set up relatively simple models that are general enough to fit on a broad range of insurance companies and that allow to conduct regulation or rating in a quantitatively more sophisticated, transparent, and standardized way, see [2].

A detailed account of the most important uses and users of DFA is given in [9]; some new perspectives are outlined in [15].

Assessment and Outlook

In view of the developments in the insurance markets as outlined in the section 'The Value Proposition of DFA', the approach taken by DFA is undoubtedly appropriate. DFA is a means for addressing those topics that really matter in the modern insurance world, in particular, the management of risk capital and its structure, the analysis of overall **profitability** and **solvency**, cost-efficient integrated risk management aimed at optimal bottom line impact, and the addressing of regulatory tax, and rating agency issues. Moreover, DFA takes a sensible point of view in addressing these topics, namely, a holistic one that makes no artificial separation of aspects that actually belong together.

The genesis of DFA was driven by the industry rather than by academia. The downside of this very market-driven development is that many features of practically used DFA systems lack a certain scientific soundness, in that modeling elements that work well, each one for itself, are composed in an often ad hoc manner, the model risk is high because of the large number of modeled variables, and company models are rather structured along the lines of accounting than along the lines of economic value creation. So, even though DFA fundamentally does the right things, there is still considerable space and need for improvements in the way in which DFA does these things.

We conclude this presentation by outlining some DFA-related trends for the near and medium-term future. We can generally expect that company-level effectiveness will remain the main yardstick for managerial decisions in the future. Though integrated risk management is still a vision rather than a reality, the trend in this direction will certainly prevail. Technically, Monte Carlo methods have become ubiquitous in quantitative analysis, and they will remain so, since they are easy to implement and easy to handle, and they allow for an easy combination of models. The easy availability of ever more computing power will make DFA even less computationally demanding in the future. We can also expect models to become more sophisticated in several ways:

The focus in the future will be on economic value creation rather than on just mimicking the cash flow structures of the company. However, substantial fundamental research still needs to be done in this area, see [14]. A crucial point will be to incorporate managerial flexibility into the models, so as to make projections more realistic. Currently, there is a wide gap between DFA-type models as described here and dynamic programming models aimed at similar goals, see [19]. For the future, a certain convergence of these two approaches can be expected. For DFA, this means that the models will have to become simpler. In scenario generation, the proper modeling of dependencies and extreme values (individual as well as joint ones) will be an important issue.

In general, the DFA approach has the potential of becoming the state-of-the-industry for risk management and strategic decision support, but it will only exhaust this potential if the discussed shortcomings will be overcome in the foreseeable future.

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(*See also* **Asset-Liability Modeling**; **Coverage**; **Interest-Rate Modeling**; **Parameter and Model Uncertainty**; **Random Number Generation and Quasi-Monte Carlo**; **Stochastic Simulation**; **Statistical Terminology**)

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