A COMPARABLES APPROACH TO MEASURING CASHFLOW-AT-RISK FOR NON-FINANCIAL FIRMS

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This article presents the results of our efforts to develop a measure of cash flow-at-risk (henceforth "C-FaR") for non-financial firms. We define C-FaR as the probability distribution of a company's operating cashflows over some horizon in the future, based on information available today. For example, if it is December 31, 2000, a company's quarter-ahead C-FaR is the probability distribution of operating cashflows over the quarter ending March 31, 2001; and its year-ahead C-FaR is the probability distribution of cashflows over the year ending December 31, 2001. These probability distributions can be used to generate a variety of summary statistics such as five-percent or one-percent "worst-case" outcomes, thereby providing corporate CFOs with answers to questions like the following: "how much can my company's operating cashflow be expected to decline over the next year if we experience a downturn that turns out to be a five-percent tail event?"

While it is easy to define the concept of C-FaR, it is much more difficult to come up with a reliable C-FaR estimate for any given company. One way to see the challenges associated with constructing a C-FaR measure is to compare it with the value-at-risk (VaR) measure commonly used by banks and other financial institutions.[1] Although there are some obvious differences between the two (for example, C-FaR focuses on cashflows while VaR focuses on asset values, and C-FaR looks out over a horizon of a quarter or a year while the horizon for VaR is typically measured in days or weeks), C-FaR is an attempt to create an analogue to VaR that can be useful for non-financial firms. Thus one might hope to be able to draw on the same basic methodological approach.

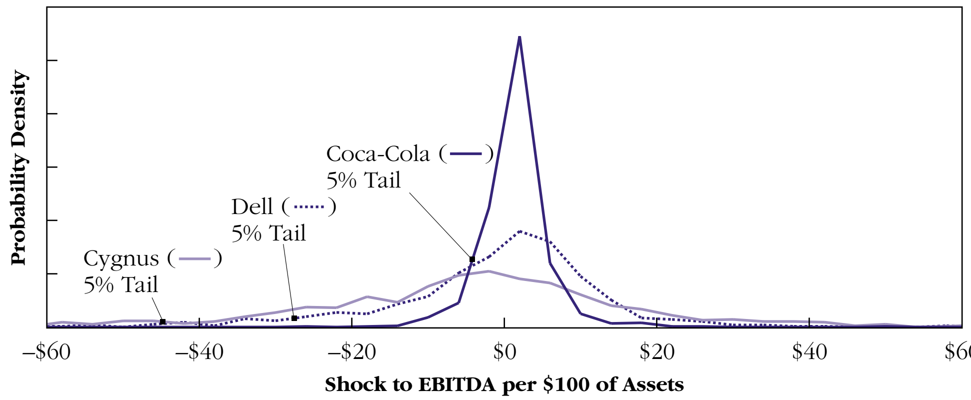
The standard approach to estimating VaR for a bank is what might be termed a "bottom up" method. One begins by enumerating each of the bank's assets—every loan, trading position, and so forth. The risk exposures (to interest rate shocks, credit risk, foreign exchange movements) of each of these assets are then quantified. Finally, these risks are aggregated across the bank's entire portfolio. Although far from perfect, this VaR methodology works reasonably well to the extent that (1) a bank can identify each of its main sources of risk and (2) these sources of risk correspond (either directly or indirectly) to traded assets for which there is good historical data on price movements. The method is perhaps best suited to evaluating the risks of a trading desk that deals in relatively liquid instruments.

Now imagine trying to apply this same bottom-up approach to a non-financial firm. For concreteness, consider the case of the computer manufacturer Dell, an example to which we will return repeatedly. How does one even begin to identify all the individual risks to Dell's cashflows? And once these risks have been identified, how can they be accurately quantified? No doubt Dell faces some of the same "tradeable" (and hence directly measurable) risks that a bank does—it has foreign exchange exposure, for example. But even if one can use standard VaR-like tools to model the quantitative

*We are grateful to Lou Guth for his support, encouragement, and advice on this project. Thanks also to Omar Choudhry and Amy Shiner for research assistance, and to Ken Froot, Paul Hinton, as well as to seminar participants at NERA for helpful comments.

1. For a detailed discussion of VaR methodology, see J.P. Morgan/Reuters, "RiskMetrics—Technical Document," Fourth Edition, 1996.

FIGURE 1
YEAR AHEAD C-FAR DISTRIBUTIONS FOR COCA-COLA, DELL, AND CYGNUS



impact of Dell's FX exposure, this risk is likely to be second-order relative to, say, the risk that Dell does a poor job of marketing and customer support and loses significant market share to Gateway and Compaq. The bottom line is that while one can—and some consultants do—attempt to implement a bottom-up VaR analogue to companies like Dell, there is a danger that such an approach will simply leave out some important sources of risk, badly mismeasure others, and thus lead to a highly inaccurate estimate of overall C-FaR.[2]

Given these difficulties with a bottom-up method, a natural alternative is to approach matters from the "top down." That is, if the ultimate item of interest is the variability of Dell's operating cashflows, why not simply look directly at their historical cashflow data? The obvious advantage of doing so is that this data should summarize the combined effect of all the relevant risks facing Dell, thereby avoiding the need to build a detailed model of the business from the ground up. Simply put, if Dell's C-FaR is high, this should be manifested in a high volatility of its historical cashflows.

Unfortunately, there is also a major problem with going this route—lack of data. The best one can do is to get quarterly data on cashflows. Thus even if one is willing to go back say five years (it is hard to imagine going back much further for Dell, given how rapidly the company is evolving), this leaves us with only 20 observations of Dell's cashflows. This is obviously an order of magnitude too few, particularly given that the goal of a C-FaR measure is to get a sense of the likelihood of extremely rare events.

But what if one could identify a group of companies that are good comparables for Dell? With 25 such companies and five years' worth of quarterly data on each, we would be up to 500 observations. With 50 comparable companies, we would have 1,000 observations. At this point, it would become possible to estimate five-percent (and even one-percent) tail probabilities with some confidence.

In this article, we describe how we have implemented this sort of top-down, comparables-based approach to C-FaR measurement. As we will explain in detail below, we use a relatively sophisticated benchmarking technique to find the best comparables for a given target company, searching for those other companies that most closely resemble our target on four dimensions: (1) market capitalization, (2) profitability, (3) industry riskiness, and (4) stock-price volatility.

One way to gauge the usefulness of this approach is to examine the extent to which it produces plausibly different answers for companies with different characteristics. In Figure 1, we plot the one-year-ahead C-FaR probability distributions for three companies: Coca-Cola, Dell, and Cygnus. (Cygnus is a $400 million market cap company engaged in the development and manufacture of diagnostic and drug delivery systems.) For comparability, all the distributions are centered on zero and are scaled in units of earnings before interest, taxes, depreciation and amortization (EBITDA) per $100 of assets. As can be seen from the figure, the distributions for the three companies are very different. For Coca-Cola a five-

2. For an example of such a bottom-up approach to measuring cashflow-at-risk, see Gregory Hayt and Shang Song, "Handle with Sensitivity," *RISK Magazine*, Vol. 8 No. 9, 1995, pp. 94-99.

percent worst-case scenario involves EBITDA falling short of expectations by $5.23 per $100 of assets; for Dell the corresponding figure is $28.50; for Cygnus it is $47.31.[3]

An obvious strength of this methodology is that—since we are looking directly at cashflow variability—by definition it produces the right answers *on average*. That is, if we run the analysis repeatedly for a number of companies, on average we will generate C-FaR estimates that are neither systematically too high nor too low. This property is not shared by any bottom-up approach. For example, if a bottom-up model ignores an important source of risk, it will produce estimates that are generally too low, perhaps substantially so.

Of course, this comparables method is not without its drawbacks. Chief among these is the fact that one cannot capture company-level idiosyncrasies that might give rise to differences in C-FaR. Thus if we create a peer group of 25 companies to estimate Dell's C-FaR, and Dell is in some way atypical of its peers (perhaps it has more overseas sales, and hence more FX exposure), this will not be captured. Another limitation of this approach is its inability to tell us much if anything about the expected impact of changes in a company's strategy on its C-FaR. For example, if Dell decides to move farther into overseas markets, we cannot say by how much this might raise its C-FaR. The ability to model these kinds of specific company-level effects is the leading advantage of the bottom-up approach used in VaR applications.

An analogy may help to bring the costs and benefits of our methodology into sharper focus. Our approach to C-FaR is analogous to the common practice of estimating the value of a company by looking at the multiples (of market-to-book, price-to-earnings, price-to-cashflow) at which its peers trade in the market. In contrast, the bottom-up approach used in VaR models is analogous to valuing a company by forecasting the cashflows from each of its operating assets, and then doing a discounted-cashflow (DCF) calculation. Neither one of these valuation approaches—comparables or DCF—can be said to strictly dominate the other; each has its strengths and weaknesses. In particular, the comparables approach to valuation will be at a comparative advantage in situations where there is not much detailed company-specific data available to make cashflow forecasts, but where there is a well-defined set of peer firms. Roughly the same can be said of our comparables approach to measuring C-FaR. Notably, in the valuation arena, comparables methods are very widely used by practitioners; even when they are not relied on exclusively, they are at a minimum seen as a useful complement to bottom-up DCF methods.

The remainder of the article is organized as follows. We begin in the next section by discussing why and how C-FaR can be useful in informing a variety of corporate finance decisions. We then go on to describe the construction of our basic model in some detail, as well as to sketch some specific extensions and applications.

WHY WOULD A COMPANY WANT TO KNOW ITS C-FaR?

In this section, we briefly discuss three broad reasons why a non-financial company might be interested in having a reasonably accurate estimate of its C-FaR.

Capital Structure Policy

The classic debt-equity choice is usually framed as trading off the benefits of debt (tax shields, increased discipline on managers) against the potential costs associated with financial distress. To operationalize this tradeoff, one needs a quantitative sense of the probability of getting into distress, given a particular capital structure. Perhaps the most important determinant of this probability of distress is the variability of cashflows—hence the usefulness of C-FaR.

To give a concrete example of how a C-FaR measure can be used in thinking about capital structure policy, consider the case of the electricity industry. This industry, which until a few years ago was largely regulated, has been subject to enormous changes as the result of rapid deregulation. Our estimates of C-FaR for the electricity industry—which we discuss in more detail below—suggest that the volatility of EBITDA for the typical firm has roughly doubled from the early 1990s to the late 1990s. Against the backdrop of these large increases

3. These differences are statistically significant. We have used bootstrapping techniques to estimate the standard errors of these five-percent tail values, and they are as follows. For Coca-Cola, the standard error of our 5.23 estimate is 0.54; for Dell the standard error of our 28.50 estimate is 2.11; and for Cygnus the standard error of our 47.31 estimate is 2.28.

in volatility, an important question to ask is whether electricity companies' capital structures have adjusted appropriately.

In 1992, the median electricity company had interest coverage, defined as the ratio of earnings before interest and taxes (EBIT) to interest expense, of 2.81. Moreover, using the results of our C-FaR analysis for the early 90s, one can show that in a five-percent worst-case scenario, coverage would fall from 2.81 to 2.23—a lower number to be sure, but one that still would seem to indicate more-than-adequate cashflow relative to debt obligations. Thus it appears that, prior to deregulation, the capital structure of the typical electricity company did not pose a very high risk of financial distress.

As of 1999, debt ratios for the industry as a whole had not changed much from their levels earlier in the decade. Indeed, the median coverage, at 2.82, was virtually identical to its value in 1992. But, with the large increase in cashflow volatility, the five-percent worst-case coverage had fallen to 1.65. This suggests that the risk of financial distress in the electricity industry, though perhaps not enormous by the standards of other industries, had become significantly greater in the later part of the decade.

The point here is not to say that the electricity companies' current capital structures are "right" or "wrong" in any absolute sense. Rather, it is just to illustrate how a C-FaR estimate can be used in conjunction with capital structure data to help formulate debt-equity tradeoffs in a more precise, quantifiable fashion. Clearly, the same apparatus can be used to think about other closely related financial policy questions such as the appropriate level of cash reserves and credit lines.

Risk Management Policy

What is the value added by risk management strategies such as the use of derivatives to hedge commodity-price exposures, or the purchase of insurance policies? Do the costs of such risk management exceed the benefits? Recent research in corporate finance has shown that risk management can indeed be an important tool for creating shareholder value. But this work also stresses that the value of risk management is greater when there is a higher probability that operating cashflows will fall to the point that important strategic investments are compromised.[4] Thus, in order to quantify the benefits of risk management, one again needs to have an accurate picture of the probability distribution of cashflows.

This point can be illustrated with a simple example. Imagine a company whose capital budget for the upcoming year is $100. The company has no ability to raise finance externally, perhaps because it is too highly leveraged to take on more debt, and is also reluctant to issue new equity. The company forecasts operating cashflows of $120. Aside from these operating cashflows, it also faces a 10% probability of being hit with a product-liability suit that will cost it $10. It can buy product liability insurance at a cost of $1.10, which represents a 10% markup over the actuarially fair value. (Fair value = 10% × $10 = $1). Should it buy the insurance?

In Scenario A, the operating cashflows of $120 are a sure thing. In this case there is no reason for the company to buy insurance; even if it is hit with the lawsuit, it will still have $110 left, which is enough to do its planned investment. However, in Scenario B, the forecast of $120 is subject to some volatility. In particular, actual operating cashflows (before any product-liability suit) will either be $150 or $90, each with probability 50%. Now insurance is potentially valuable, because half of the time it kicks in when the company has a cash shortfall relative to its investment needs, and hence will be underinvesting. To be more specific, assume further that each dollar invested yields an NPV of $1.40, so that a failure to invest a dollar costs the company 40 cents in forgone value. In this case the company would be willing to pay up to $1.20 for the insurance policy.[5]

The moral of the example is simple: Holding fixed the risks to be hedged (the product liability risk, in the example), the greater are the unhedgeable background risks, as measured by C-FaR, the greater is the value of risk management.

4. This research includes: Kenneth A. Froot, David S. Scharfstein and Jeremy C. Stein, "Risk Management: Coordinating Corporate Investment and Financing Policies," *Journal of Finance*, vol. 48, 1993, pp. 1629-1658; René M. Stulz, "Rethinking Risk Management," *Journal of Applied Corporate Finance*, vol. 9, 1996, pp. 8-24; and Froot and Stein, "Risk Management, Capital Budgeting, and Capital Structure Policy for Financial Institutions: An Integrated Approach," *Journal of Financial Economics*, vol. 47, 1998, pp. 55-82.

5. The .20 premium to fair value represents the 50% probability of the low cashflow event, times the 10% probability of a lawsuit, times the $4 of added net present value that the company gets from being able to invest $10 it otherwise wouldn't have.

Disclosure: Managing Investors' Expectations About Earnings Volatility

It is a fact of life that some investors, as well as analysts, are extremely concerned about volatility in reported quarterly earnings, and that this concern translates into pressure on management to meet earnings targets. By disclosing the results of a comparables-based C-FaR analysis to investors or analysts ahead of time, a company may be able to help put earnings shocks into a credible, objective, peer-benchmarked perspective. In particular, one could make statements like the following: "For other companies in our peer group, an X% deviation of quarterly earnings from expectations is not at all atypical—indeed, it occurs roughly Y% of the time."

BUILDING THE MODEL

We begin by assembling quarterly income-statement and balance-sheet data from Compustat. In our baseline analysis, we pool together data from firms in all non-financial industries. However, our model can also be applied to individual well-defined industries in which there are enough firms. Electricity companies represent one such industry; we will review this industry-specific application later.

Our basic measure of operating cashflow is earnings before interest, taxes, depreciation, and amortization (EBITDA). Alternatively, one can use earnings before interest and taxes (EBIT). The results are virtually identical in either case, which is not surprising given that there is very little unpredictable variation in depreciation and amortization a quarter or a year ahead. To allow for comparability across firms, we scale EBITDA by start-of-period book assets.

We clean the data by eliminating firms with very tiny values of book assets (those in the lowest five percent of the distribution each quarter), so as to avoid situations where the ratio EBITDA/Assets becomes unboundedly large.[6] We also screen out firm-quarters where property plant and equipment (PP&E) changes by more than 50% in a quarter. The idea here is to eliminate large mergers or other dramatic changes in a company's asset base, which are not surprises from the company's point of view, but which can potentially induce a great deal of volatility in measured EBITDA/Assets. We have experimented with setting this PP&E screen at different tolerances (e.g., 20%, 30%, and 40%) and our results are essentially identical.

The First-Step Forecasting Regression

In order to measure how much cashflow deviates from expectations, one needs to have a forecast of expected cashflow. In our case, this means we need a model to forecast cashflow both a quarter into the future, as well as a year into the future. To do so, we use a very simple autoregressive specification. For our quarterly forecast, we regress EBITDA/Assets in quarter t against four lags of itself: that is, against EBITDA/Assets in quarters t–1, t–2, t–3, and t–4. We also add to the regression quarterly dummy variables to account for possible seasonality in the data. In any quarter t, the model is fit using the past five years' worth of data.

Panel A of Table 1 gives an example of such a regression, which is fit using data from 1991 to 1995. As can be seen, the simple autoregressive structure does a good job of forecasting the next quarter's EBITDA/Assets, attaining an R^2 of 58%. Indeed, we have experimented with a variety of more complicated models, and in no case were we able to do significantly better on this score.[7]

To forecast a year into the future, we use the same right-hand-side variables as before: EBITDA/Assets in quarters t–1, t–2, t–3, and t–4, as well as the quarterly dummies. The only modification is that now the dependent variable is the sum of EBITDA in quarters t, t+1, t+2 and t+3, all divided by assets at the start of quarter t. That is, we are now forecasting the next full year's worth of EBITDA. The results from this regression are shown in Panel B of Table 1. Again, the R^2 is quite high, this time reaching 63%.

It is important to be clear as to the purpose of these forecasting regressions. Our ultimate goal is not to make more accurate quarter-ahead or year-ahead predictions of expected cashflow than could be produced by, say, industry experts or well-informed company insiders. Rather, our interest is in making statements about the entire probability distribution of shocks to cashflow, particularly the tails

6. As of 1999, this screen corresponds to throwing out firms with book assets below roughly $3 million.

7. Among the things we tried were: adding up to eight lags of EBITDA/Assets; allowing for separate lag coefficients for each 3-digit SIC industry; adding firm and/or industry dummies; and adding stock returns as an additional explanatory variable. None of these yielded a significant increase in out-of-sample predictive power.

TABLE 1
FIRST-STEP FORECAST REGRESSIONS FOR THE 5 YEARS 1991-1995

	EBITDA/Assets lagged:			
	1-Quarter	2-Quarters	3-Quarters	4-Quarters
PANEL A. FORECASTING ONE-QUARTER AHEAD EBITDA/ASSETS FOR 1996 Q1				
Coefficient	0.4118	0.1214	0.0845	0.2626
(T-Statistic)	(108.95)	(30.29)	(22.49)	(82.86)
R-Squared = 0.58				
PANEL B. FORECASTING ONE-YEAR AHEAD EBITDA/ASSETS FOR 1996				
Coefficient	1.6221	0.9927	0.5554	0.4393
(T-Statistic)	(110.95)	(63.96)	(38.59)	(36.68)
R-Squared = 0.63				

of this distribution. But to define a shock, one needs a benchmark for what cashflow is expected to be in the absence of a shock. In other words, our shocks correspond to forecast errors—to deviations of cashflow from their expected values. Thus the cashflow forecasts we construct are not an end in and of themselves, but rather a necessary ingredient to construct these forecast errors.

A concrete example may be helpful. Suppose we want to construct the quarter-ahead forecast error for company XYZ for the first quarter of 2000. We begin by taking the perspective of December 31, 1999. Using data from the prior five years (December 1994-December 1999), we fit our model and make a forecast for XYZ's EBITDA/Assets for the first quarter of 2000. Let's say this forecast is .05—that is, our regression model predicts that XYZ will have EBITDA of $5 for every $100 of assets in the first quarter of 2000. The forecast is then compared to the actual realized value of EBITDA/Assets for XYZ in the first quarter of 2000, thereby generating a forecast error. So if XYZ's actual EBITDA/Assets in the first quarter of 2000 turns out to be .04, we would say the forecast error is –.01 (actual of .04 minus forecast of .05). This is the unanticipated shock to XYZ's EBITDA/Assets. The procedure for calculating year-ahead forecast errors is the same, except in this case we would compare XYZ's EBITDA/Assets for the full year 2000 to the value forecast as of December 1999.

We repeat this procedure for every company quarter in our database. This gives us a very large pool of forecast errors. For example, even if we restrict ourselves to forecast errors from the most recent six years (1994-1999), we have roughly 85,000 observations.

Sorting the Forecast Errors Based on Company Characteristics

The big pool of 85,000 forecast errors represents a hodgepodge of data from all different types of companies. In order to learn something about the probability distribution of cashflows for a particular company, we want to dip into this pool and extract only those forecast errors that come from its "peer group," suitably defined. In other words, we need to subdivide the 85,000 observations into subsamples, where each subsample is composed of firms with roughly similar characteristics. To do so, we need to have an idea of what the salient firm characteristics are—i.e., which characteristics matter for forecast-error volatility.

After substantial experimentation, we have settled on four characteristics that seem to be most strongly associated with patterns in forecast-error volatility.[8] The first of these is market capitalization. There is a very strong, systematic tendency for larger firms to have smaller forecast errors, most likely as a result of the fact that larger firms are better diversified. The second key characteristic is profitability, measured as the average value of EBITDA/Assets over the prior four quarters. The third is the riskiness of industry cashflow and the fourth is stock-price volatility, calculated using daily stock price data over the prior quarter.

We create subsamples based on these four characteristics as follows. Beginning with the full pool of roughly 85,000 forecast errors, we first sort firms into three buckets based on market capitalization. All forecast errors coming from firms in the bottom one-third of the sample by market cap in any

8. This experimentation involved taking the log of squared forecast errors, and regressing them against a variety of candidate variables.

given quarter are assigned to "market-cap bucket 1," those from the middle one-third of the sample are assigned to "market-cap bucket 2," and so forth. Next, we further subdivide each market cap bucket into three sub-buckets according to whether an observation corresponds to a firm in the bottom, middle, or top one-third of the bucket by profitability. At this point we have nine sub-samples.

These nine subsamples are then further subdivided by three again, according to a measure of industry cashflow risk.[9] Finally, we subdivide the resulting 27 subsamples once more, this time based on their stock-price volatility. When all is said and done, we have 81 bins, corresponding to three-way splits on each of four dimensions. In each of these 81 bins, there are approximately 1,000 forecast errors. The hope at this point is that within each of the 81 bins, the forecast errors come from a relatively homogeneous group of firms, matched on the characteristics that matter most.

To the extent that this homogeneity assumption holds true, we now have a very powerful non-parametric way to assess C-FaR for any given firm. Simply locate which of the 81 bins the firm in question belongs to, based on its current values of market cap, profitability, industry risk, and stock-price volatility. Then the roughly 1,000 forecast errors in that bin can be thought of as describing the firm's empirical C-FaR distribution.

This procedure is how we came up with the plots for Coca-Cola, Dell and Cygnus shown in Figure 1 earlier. For example, Coca-Cola is in the top one-third of the sample with respect to market cap. Within market cap bucket 3, it is also in the top one-third with respect to profitability. On the other hand, it is in the lowest third of its subsamples with respect to both industry risk and stock-price volatility. Thus overall, Coca-Cola is assigned to the bin that we denote {3, 3, 1, 1}. The plot of Coca-Cola's year-ahead C-FaR distribution in Figure 1 is nothing more than the histogram of the year-ahead forecast errors in bin {3, 3, 1, 1}. A similar logic applies for Dell and Cygnus, which are assigned to bins {3, 3, 3, 3} and {2, 1, 3, 3} respectively.

The empirical probability distributions of the sort shown in Figure 1 give us a great deal of flexibility. Since the data trace out the entire distribution, we do not need to rely on any assumptions about normality.[10] Instead, to evaluate the five-percent tail for any given company, we simply look at the fifth percentile of the empirical distribution.

Table 2 is a grid that reports the five-percent values of the C-FaR distribution, in units of EBITDA per $100 of assets, for each of the 81 bins. Panel A looks at quarter-ahead shocks, while Panel B looks at year-ahead shocks. The cells corresponding to our example companies—Coca-Cola, Dell and Cygnus—have been highlighted in the table.

Whether one looks at Panel A or Panel B of Table 2, several distinct patterns emerge. Smaller firms, as well as those in riskier industries or with higher stock-price volatility, all show markedly more extreme tail values. These patterns are all what one would expect, though it may be surprising just how strong they are in some cases. The effect of profitability is a bit more subtle. There is a general tendency for unprofitable firms to have riskier cashflows, which one might interpret to be a consequence of operating leverage. But this tendency does not hold across all the cells in the grid.

Just to clarify the interpretation of the units in Table 2, consider the {3, 3, 3, 3} cell in the lower right-hand corner of Panel B, where one finds the year-ahead number for Dell. This number is –28.50, which should be read as saying that, in a five-percent worst-case year, Dell's EBITDA would fall short of expectations by $28.50 for every $100 of book assets that it has. For example, applying the model at the start of Dell's 1999 fiscal year, when its book assets (net of cash and securities) stood at $3,696 million,[11] the conclusion is that a five-percent worst-case scenario for 1999 would involve an EBITDA shortfall of $1,053 million (1,053 = 3696 × .285) To get a sense of proportion, this figure can be compared to Dell's actual realized 1999 EBITDA of $2,419 million. Assuming that $2,419 was also the fore-

9. We generate this measure of industry cashflow risk by taking the log of squared residuals from our first-stage model, and regressing them on: 1) market cap, 2) profitability, 3) stock-price volatility, and 4) dummy variables for each 3-digit SIC code. The higher the coefficient on an industry's dummy, the riskier that industry is deemed to be.

10. VaR models, in contrast, are heavily dependent on normality assumptions. Interestingly, our empirical C-FaR distributions appear to be fatter-tailed than normal distributions, as well as somewhat right-skewed.

11. In applying the model to Dell, we have chosen to multiply through by its book assets net of cash and securities, because: (1) in theory, EBITDA volatility should be proportional to the level of operating (i.e., non-cash) assets; and (2) Dell's level of cash and securities, at 46.3% of book assets, is highly anomalous relative to the overall Compustat sample, for which the median value of cash and securities to assets is only about 6%.

TABLE 2

PANEL A. QUARTER-AHEAD 5% C-FaR TAILS*

Stock Volatility Bucket	Market Cap Bucket	Industry Bucket 1			Industry Bucket 2			Industry Bucket 3		
		EBITDA/Assets Bucket 1	2	3	EBITDA/Assets Bucket 1	2	3	EBITDA/Assets Bucket 1	2	3
1	1	–7.63	–3.12	–3.32	–10.29	–4.30	–3.84	–11.70	–5.20	–6.15
	2	–1.93	–1.37	–1.69	–6.96	–2.18	–2.77	–8.38	–3.22	–4.49
	3	–1.21	–1.11	–1.46[a]	–1.16	–1.45	–1.71	–2.52	–2.13	–3.14
2	1	–7.13	–3.99	–3.91	–11.97	–5.49	–5.19	–13.05	–6.51	–6.96
	2	–3.68	–1.76	–2.34	–8.96	–2.48	–4.24	–9.83	–4.81	–6.23
	3	–0.96	–1.14	–1.84	–1.27	–1.19	–2.40	–3.22	–2.12	–3.80
3	1	–7.87	–4.13	–4.94	–11.16	–5.59	–6.09	–12.93	–7.88	–7.56
	2	–6.92	–2.59	–3.09	–11.06	–4.84	–6.05	–14.41[c]	–6.08	–7.53
	3	–1.51	–1.66	–2.47	–2.65	–2.12	–4.10	–6.05	–3.99	–6.63[b]

PANEL B. YEAR-AHEAD 5% C-FaR TAILS*

Stock Volatility Bucket	Market Cap Bucket	Industry Bucket 1			Industry Bucket 2			Industry Bucket 3		
		EBITDA/Assets Bucket 1	2	3	EBITDA/Assets Bucket 1	2	3	EBITDA/Assets Bucket 1	2	3
1	1	–22.77	–10.45	–11.31	–32.29	–14.35	–14.99	–44.68	–16.31	–23.79
	2	–6.74	–4.79	–6.64	–16.60	–6.94	–12.53	–30.71	–8.94	–13.59
	3	–3.32	–3.58	–5.23[a]	–3.97	–5.00	–5.91	–5.28	–4.78	–8.60
2	1	–23.43	–14.44	–13.32	–38.67	–19.49	–21.19	–39.07	–23.08	–31.46
	2	–14.41	–7.94	–9.83	–30.81	–10.38	–19.46	–37.88	–15.44	–26.66
	3	–3.64	–4.87	–6.98	–4.46	–5.31	–13.85	–9.86	–6.38	–12.91
3	1	–24.72	–13.92	–19.77	–30.47	–19.58	–25.13	–43.87	–23.64	–36.02
	2	–25.63	–11.55	–14.25	–37.65	–19.85	–31.76	–47.31[c]	–23.83	–31.78
	3	–7.05	–8.57	–13.11	–11.26	–10.86	–23.37	–20.88	–15.19	–28.50[b]

*For a firm with $100 in assets, each cell shows how big a negative shock to one-quarter ahead EBITDA (Panel A) or one-year ahead EBITDA (Panel B) occurs with 5% probability.
a. Bucket containing Coca-Cola.
b. Bucket containing Dell.
c. Bucket containing Cygnus.

casted value of EBITDA at the start of 1999, then we could say that in the five-percent worst case, EBITDA would fall 43.5% below expectations (1,053/2,419 = 43.5%).

Note that any statements that we make about EBITDA can be easily translated into statements about EBIT, or about after-tax net income. To the extent that Dell can perfectly forecast its depreciation and amortization a year ahead, its unanticipated EBIT shortfall is exactly the same as its EBITDA shortfall. And to get its net income shortfall, all one has to do is multiply by one minus the tax rate. Thus assuming a tax rate of 35%, the five-percent worst-case net income shortfall is $684 million (684 = .65 × 1,053), which is equivalent to 41.1% of actual realized 1999 net income.

TABLE 3
PARTIAL LIST OF C-FaR COMPARABLE COMPANIES FOR DELL

3COM Corp	Cirrus Logic Inc	Micro Warehouse Inc
Adaptec Inc	Cisco Systems Inc	Micron Electronics Inc
Adobe Systems Inc	Compaq Computer Corp	Network General Corp
Auspex Systems Inc	Computervision Corp	Oracle Corp
Autodesk Inc	Compuware Corp	Peoplesoft Inc
Bed Bath & Beyond Inc	Dialogic Corp	Project Software & Dev Inc
BMC Software Inc	Fore Systems Inc	S3 Incorporated
Broderbund Software Inc	Gateway Inc	Symantec Corp
Cheyenne Software Inc	Informix Corp	Systems&Computer Tec
Chipcom Corp	Legato Systems Inc	Williams-Sonoma

A Closer Look at Dell's Peer Group

At this point, our four-characteristic sorting method of creating a peer group for any company may seem like something of a black box. What kind of comparables actually come out of this approach? As an illustration, Table 3 presents a partial list of the comparable companies that the model generates for Dell—i.e., some of Dell's peers in bin {3, 3, 3, 3}. Many of the natural suspects show up, such as Dell's closest competitors Compaq, Gateway, and Micron, as well as other large, profitable high-tech companies like Cisco. But not all of the comparables are what one might have expected. For example, retailers like Bed Bath & Beyond and Williams-Sonoma make the list as well. Again, they are there because they resemble Dell in terms of market cap, profitability, and stock-price volatility. And even though they are in a quite different industry, it is one that historically has had cashflow volatility comparable to that of Dell and its high-tech brethren.

Variations on the Basic Model

The basic comparables approach to C-FaR that we have described can be modified in a number of ways. Here we briefly discuss a couple of examples.

Customized, centered peer groups. Consider two firms, one in the 70th percentile of the market-cap distribution, and one in the 90th percentile. Our baseline methodology treats these firms as identical for market-cap purposes, sticking them both in the bucket corresponding to the top one-third of the sample (i.e., the bucket for all firms above the 67th percentile). On the other hand, the 70th percentile firm goes in a completely different bucket than one in the 65th percentile, because they are on opposite sides of the cutoff. This would seem to be an arbitrary and unattractive feature.

An alternative approach is to create customized, "centered" peer groups for any given firm we study. For example, if we are looking at a firm in the 70th percentile by market cap, we could create for it a customized market-cap bucket, such that this firm fits right into the middle of the bucket. In other words, the market-cap bucket for our 70th percentile firm would include all firms with market caps between approximately the 53rd percentile and the 87th percentile. A similar approach can be used when we sort on the other three characteristics. Although this involves re-running the model each time we look at a new firm–as opposed to just picking firms out on a once-and-for-all grid of the sort shown in Table 2—it arguably does a better job of creating representative peer groups.

Single-industry analyses. In our baseline C-FaR model, we analyze companies from all non-financial industries jointly. But this is not necessary. Indeed, in some cases it may make more sense to look at a single well-defined industry in isolation. This is particularly true if (1) the industry has enough firms to create a decent-sized pool of forecast errors and (2) there are specific questions about this industry that cannot be answered if it is pooled together with others.

Consider the case of the electricity industry. As noted above, this industry has undergone rapid deregulation over the past several years. In light of this deregulation, a natural question to ask is: how has the C-FaR of the typical electricity company changed over the course of the 1990s? To address this question, we begin by taking the roughly 100 electricity companies in SIC codes 4911 and 4931 and creating a pool of forecast errors just for them. Given that we want to see how things have changed over the past decade, we now allow for 10 years' worth of forecast errors, from 1990-1999. In total, this yields about 3,400 forecast errors for this industry.Next, we divide our ten-year sample period into thirds—

TABLE 4
C-FAR ANALYSIS OF ELECTRICITY INDUSTRY

PANEL A. 5% YEAR-AHEAD VALUES PER $100 OF ASSETS FOR INDUSTRY AS A WHOLE

Early 90's (1990Q1-1993Q1)	Mid 90's (1993Q2-1996Q2)	Late 90's (1996Q3-1999Q4)
–1.80	–2.11	–3.30

PANEL B. 5% YEAR-AHEAD VALUES PER $100 OF ASSETS FOR SUBSAMPLES IN LATE 1990'S

	Low Profitability	High Profitability
Low Stock Price Volatility	–2.79	–2.34
High Stock Price Volatility	–5.11	–2.67

corresponding to the early, mid and late 1990s—and examine separate C-FaR distributions for each. Panel A of Table 4 shows the year-ahead five-percent tails for each of the three sub-periods. As can be seen, this value rises from –1.80 in the early 90s to –2.11 in the mid 90s, to –3.30 in the late 90s—i.e., it roughly doubles over the course of the decade.

Another question that one might ask is: how do the C-FaR distributions vary for electricity companies with different characteristics? Naturally, we no longer have enough data to chop this much-smaller pool of forecast errors into 81 separate bins. But there is no longer any need to. Firstly, the observations are all from firms in the same industry, so there is no need to do an industry cut. Moreover, most are relatively large (as compared to the overall Compustat sample), so there is less need to sort on market cap as well. Instead, we streamline our sorting procedure so that we just do a pair of two-way sorts—one on profitability and one on stock-price volatility—thereby dividing the pool of forecast errors into four subsamples.

Panel B of Table 4 reports the results of this procedure implemented only on the late-1990s data. As can be seen, the general tendencies that we identified in the full Compustat sample (higher cashflow volatility among firms with low profitability and high stock-price volatility) hold true within the electricity sector as well. In particular, those firms that land in the low-profitability/high-stock-price-volatility bin have a year-ahead five-percent tail that is roughly twice as large as the firms in any of the other bins.

CONCLUSIONS

We believe that our top-down, comparables-based approach to estimating C-FaR offers a number of practical advantages. First and foremost, by looking directly at the ultimate item of interest—cashflow variability—the model naturally produces estimates that, within any given peer group, are correct on average. In contrast, with a bottom-up approach, one cannot be sure that the estimates are not severely biased. Second, the model is non-parametric, and thereby avoids imposing the highly unrealistic assumption that shocks to cashflow are normally distributed. Finally, once the model is built, it can be easily and at relatively low cost applied to any number of non-financial companies.

Of course, none of this is to claim that our approach dominates the alternative of building a company-specific C-FaR model from the bottom up. Rather, the two approaches can be thought of as complementary. For example, our model can be used to provide a "reality check" on the results produced by an in-depth bottom-up analysis. Again, the analogy to valuation practices is informative. Comparables methods are widely (though not exclusively) used by practitioners to value companies. And in spite of their inability to factor in certain types of company-specific information, it would be hard to argue that they do not represent an important part of the pragmatic person's valuation toolkit. We hope that our approach to estimating C-FaR will prove to be similarly useful.

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