Forecasting Earnings and Earnings Risk: An Econometric Approach

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Presented by:

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Abstract

DRI-WEFA is developing statistical models to forecast earnings and estimate future earnings volatility for a broad range of economic sectors, industries, and individual companies. Our methodology uses a "top-down" econometric framework that integrates historical company financial information with DRI-WEFA's extensive repository of macroeconomic and industry-level economic history and forecasts. For each sector and industry, we identify a set of underlying fundamental economic drivers that display both high correlation with historical earnings behavior and have significant out-of-sample predictive power. Using this framework we can project future earnings in a way that is completely consistent the underlying economic and industry outlooks DRI-WEFA develops on a regular basis. In addition, the methodology supports the rapid generation of alternative forecast scenarios. We then apply Monte Carlo simulation techniques to estimate the complete probability distribution of future earnings. This allows us to generate economically consistent forecasts of earnings risk ("volatility") and supports a wide range of stress testing and sensitivity analyses. This research introduces our basic forecasting and quantitative simulation methodology, and shows examples of how these methods can be applied for both equity and credit analysis.

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Introduction and Motivation

The analysis and prediction of company earnings is indisputably a core element of modern investment research. Investment firms expend significant resources on their efforts to monitor, analyze, and ultimately predict company earnings. The reasons for this intense scrutiny are clear — both in theory and practice earnings are seen as a fundamental determinant of stock returns. Yet despite this frenzy of effort, there arguably remain fundamental shortcomings in how many analysts and investors predict earnings. The majority of earnings estimation is done in a "bottom-up" fashion, in which analysts most typically use "accounting" frameworks to construct income and balance sheet estimates of a company at some specified time in the future. From these, earnings forecasts, P/E ratios, target share prices, and other common metrics can be calculated. The critical inputs for these estimates are usually created by some combination of (1) interaction with company management, suppliers, competitors, and customers; (2) ongoing surveillance of the key industry trends and conditions; and (3) the opinions of competing analysts. Typically these estimates are as closely tied to the analyst as to the methodology, and for the most part are not statistical in nature. Moreover, the underlying economic factors driving the firm's earnings process are often not stated explicitly, or are introduced into the earnings estimation procedure in a less than rigorous fashion. So even though one can argue that share prices implicitly reflect the effects of these factors (through the market's expectations of discounted future earnings), in many applications it is important to be able to explicitly enumerate and attempt to quantify these driving factors. As such this bottom-up accounting approach is limited. The upshot is that the conventional approach to earnings estimation makes it difficult to consistently track analysts' performance, replicate their methods, isolate the effects of changing economic or institutional conditions on their estimates, and extend their predictions beyond a relatively short time horizon. And even more problematic of late is the purported bias in the earnings estimates published by investment banking firms.

There is also an interesting additional problem that can and should be considered. By their very nature, earnings forecasts, like predictions of any economic variable, involve a potentially high degree of uncertainty[1]. The ability to explicitly quantify this uncertainty is closely tied to the idea of formally estimating risk, and has become an increasingly important component of many asset pricing models, quantitative investment decision rules, and portfolio optimization procedures. Under the traditional approach, developing consistent measures of earnings risk, *i.e.*, measures that may be meaningfully compared across firms, over time, or across analysts, is highly problematic. Thus while we can observe differences in published analysts' expectations, we cannot easily explain why such differences exist, determine if the differences are meaningful, or understand how such differences can be used to improve security selection. Answers to fundamental and

[1] There is a wise adage in economic forecasting that states: "The only thing we know for certain about a forecast is that it will be wrong." Given this, the really important question is *how* wrong? This leads directly to the idea of estimating the probability distribution of earnings forecasts, from which we can readily generate measures of earnings risk (volatility).

often-posed questions such as "how does the onset of a recession affect the risk of this firm's future earnings" are therefore elusive.

In response, this research aims to address some of these shortcomings by offering a "top-down" oriented econometric approach to earnings forecasting that can be used as a compliment to more traditional "bottom-up" approaches. Note that we do not offer this approach as a replacement or stand-alone alternative to conventional approaches. Instead we suggest that the econometric approach can fill a critical void in the investment decision-making process and support a more disciplined way of constructing portfolios. In addition, it directly addresses many of the key shortcomings of traditional earnings estimation methodologies and, as we shall discuss in greater detail below, holds promise as a way of meaningfully quantifying earnings risk.

Our methodology uses an econometric framework that integrates historical company-level financial information with DRI-WEFA's extensive repository of macroeconomic and industry-level economic history and forecasts. At this stage of our research program, we limit ourselves to forecasting earnings for broad economic sectors. Nonetheless this should be sufficient to introduce the basic ideas. The methodology is readily extendible to more disaggregate industries, sub-industries, peer groups, and in many cases, individual firms. For each sector, we identify a set of underlying fundamental economic drivers that display both high correlation with historical earnings behavior and have significant out-of-sample predictive power. We then use regression analysis to estimate an equation with which we project future earnings in a way that is completely consistent the underlying economic and industry outlooks DRI-WEFA develops on a regular basis. The methodology, by its nature, identifies and provides measure of the influence of key economic drivers. It also supports the rapid generation of alternative forecast scenarios. We then apply Monte Carlo simulation techniques to estimate the probability distribution of future earnings. This allows us to generate economically consistent forecasts of earnings risk ("volatility") and efficiently supports a wide range of stress testing and sensitivity analyses. These forecasts and volatility estimates have obvious uses in both equity and credit analysis.

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Introduction

- Assessment of prevailing "bottom-up" approach
- Review a complimentary "top-down" econometric approach to forecasting earnings and earnings volatility
- Promising way to generate key inputs into:
  - Portfolio construction
  - Credit assessment
  - Quantitative risk management

Earnings Forecasts: Current Practice

- Most earnings estimation is “bottom-up”
- Use accounting framework to construct estimates of future financial statements
- Key Factors
  - Interaction with managers, customers, suppliers, competitors
  - Surveillance of key industry trends
  - Opinions of competing analysts

Potential Shortcomings

- Underlying economic factors that drive earnings not always explicit
- Estimation procedures are often "fluid", not very rigorous, hard to replicate
- Dealing with multiplicity of economic influences
- Extending prediction intervals
- Difficult to *separate analysis from analyst*
- Bias

… More "Bottom-Up" Shortcomings

- **Hard to quantify *inherent uncertainty* in the earnings estimation**
- **Difficult to:**
  - **Compare estimates**
  - **Account for difference**
  - **Explain success or failure**
  - **Construct "what-if" scenarios**
- **How do we get a useful notion of "risk"?**

Our Approach

- "Top-Down" orientation
- Identify explicit linkages between earnings and the fundamental *economic drivers* of earnings
- Monte Carlo simulation to estimate risk and volatility

Potential Advantages

- Relationship between earnings and earnings drivers made explicit
- Statistically testable, less prone to analyst bias
- Direct estimates of risk
- Scenario, simulation, stress-testing
- Forecasts and risk estimates consistent with underlying economic assumptions
- Compliment not substitute!

Overview of Earnings Forecasting Models

- Forecasts EBITDA for across S&P/MS GICS
  - 10 Economic Sectors
  - 23 Industry Groups
  - 59 Industries
  - 123 Sub-Industries
- Driven off DRI-WEFA Macro and Industry Forecasts
- 5-year forecast horizon, quarterly frequency
- Focus today on sector-level example
- Still research in progress (02Q1)

Overview of Methodology

Compustat Firm-level Financial History

DRI-WEFA IAS/Macro/Intl History & Forecast

Econometric Forecasting Model

Generate Conditional Multi-Year Earnings Forecast.

Monte Carlo Simulation

Estimate Conditional Distribution of earnings Forecasts

Distribution of Future Earnings

Consistent, Objective Conditional Risk Measures

Earnings Drivers

- **Identify fundamental economic factors that drive production, sales, pricing decisions. Criteria:**
  - **Consistent with economic theory**
  - **Historical correlation/statistical properties**
  - **Out-of-sample predictive power**
- **Unique alternative measure of industry performance from the DRI-WEFA Industry Analysis Service (IAS)**

Industry Analysis Service

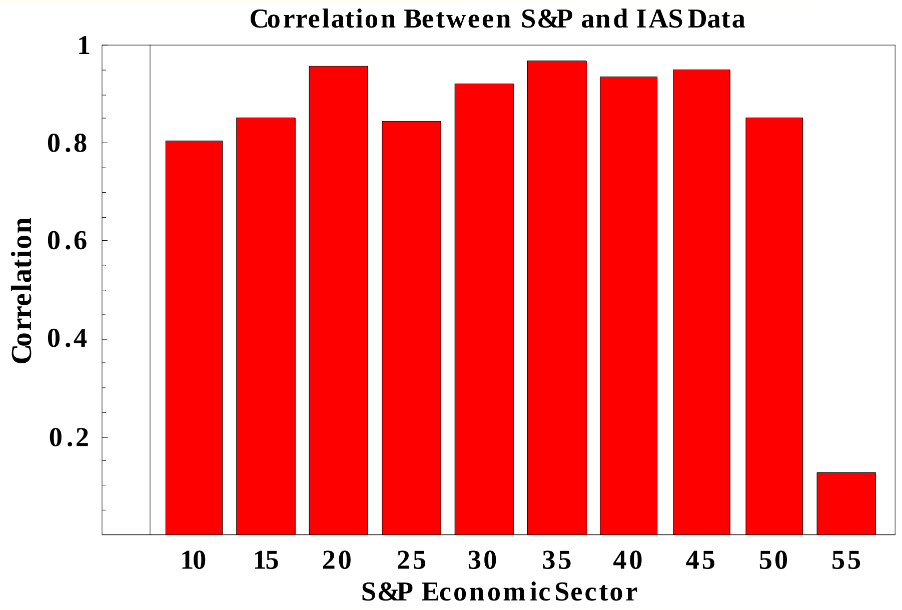
- Forecasts industrial activity for 147 U.S. Industries
  - MFG – Demand, production, shipments, inventory, prices,labor/materials costs, gross operating margin (GOM)
  - Non-MFG – Production, prices, labor/materials costs, GOM
- Uses combined Input-Output and Econometric forecasting methodology Foundation
- Describes production inter-relationships between industries
- Result: GOM is an independent alternative measure of underlying "economic earnings"

Data Compatibility

- **Statistical comparison of IAS data with Compustat financials**
  - **IAS gross operating margins (GOM) vs. Compustat EBITDA**
  - **Gather data on 147 IAS sectors and nearly 9,900 individuals U.S. companies**
  - **Mapped and aggregated IAS sectors into the 10 major Economic Sector GICS**
  - **Ten years of quarterly data, from 1991 – 2000**

Sector Correlations

Sector	Num.	Correlation
Energy	10	0.81
Materials	15	0.88
Industrials	20	0.96
Cons. Discret.	25	0.86
Cons. Staples	30	0.90
Health Care	35	0.97
Financials	40	0.94
IT	45	0.85
Telecomm	50	0.76
Utilities*	55	0.11



* The low correlation is the result of seasonality. The seasonally-adjusted correlation is 0.6

Basic Regression Results

Sector	Num.	Adj-R^2
Energy	10	0.65
Materials	15	0.76
Industrials	20	0.91
Cons. Discret.	25	0.72
Cons. Staples	30	0.81
Health Care	35	0.93
Financials	40	0.87
IT	45	0.72
Telecomm	50	0.59
Utilities	55	---

Result of simple regression of Sector EBITDA on Sector GOM

Example: Energy Sector Forecasting Model

Econometric model for Sector 10 (Energy) :

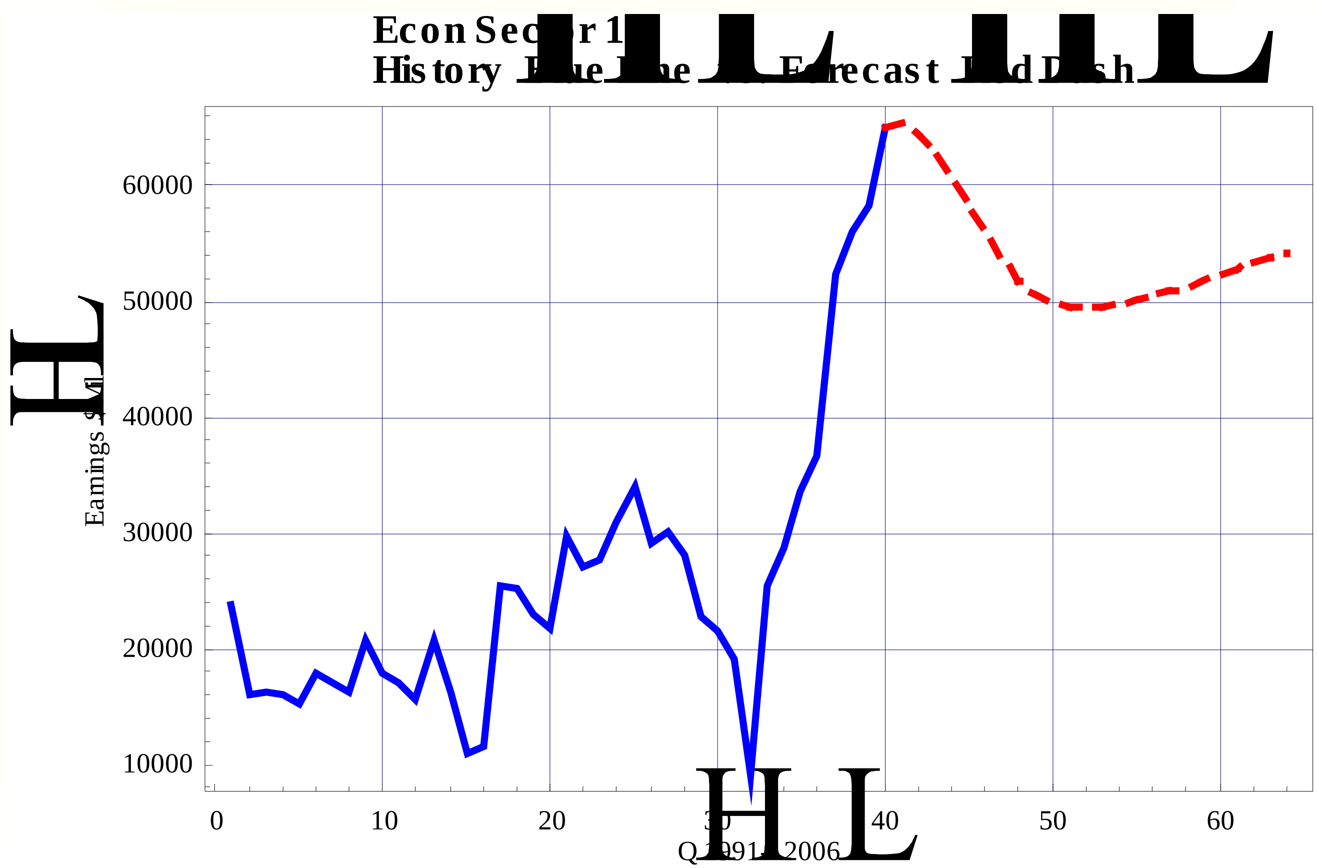
$$\text{EBITDA}_t = -27341 + 147.7 * \text{GOM}_t + 1641.6 * \text{pOIL}_t + 0.50 * \text{EBITDA}_{t-4}$$

(-5.5) (2.2) (5.1) (3.3)

Adj-R^2 = 0.82

(T-statistics in Parentheses)

Sample Energy Sector Forecast



Monte Carlo Simulations

- GOAL: Estimate the probability distribution of future sector earnings
- Monte Carlo procedure:
  - Calculate the Variance/Covariance Matrix for the set of ten sector regression residuals
  - Generate a vector of random variables (our "shocks") using a MVN distribution with mean zero and covariance vector equal to above. Do this for every quarter in the forecast interval
  - Add i^{th} shock to i^{th} forecast equation and solve – this creates a new "shocked" forecast path
  - Repeat a large number of times (>5000)
- Estimate distribution and other statistics

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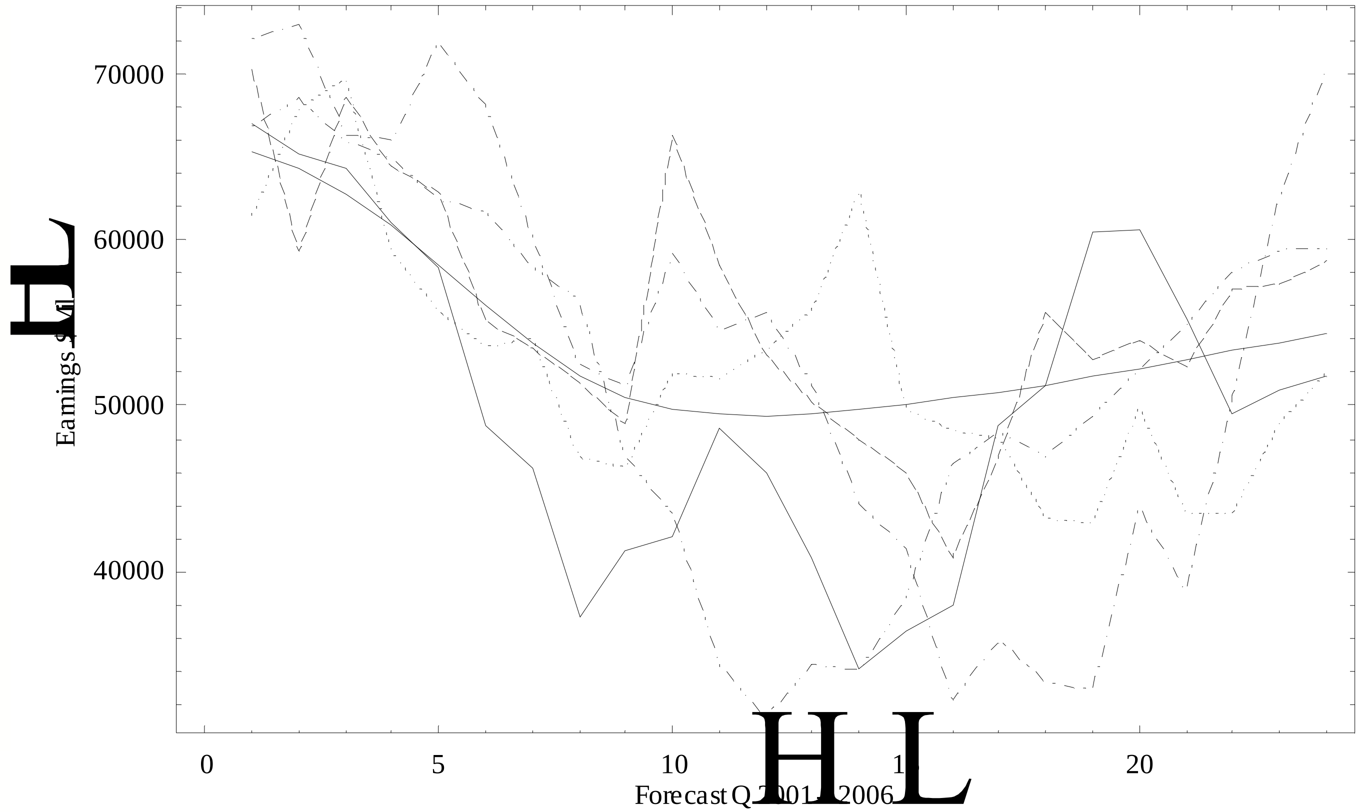
Simulation Results

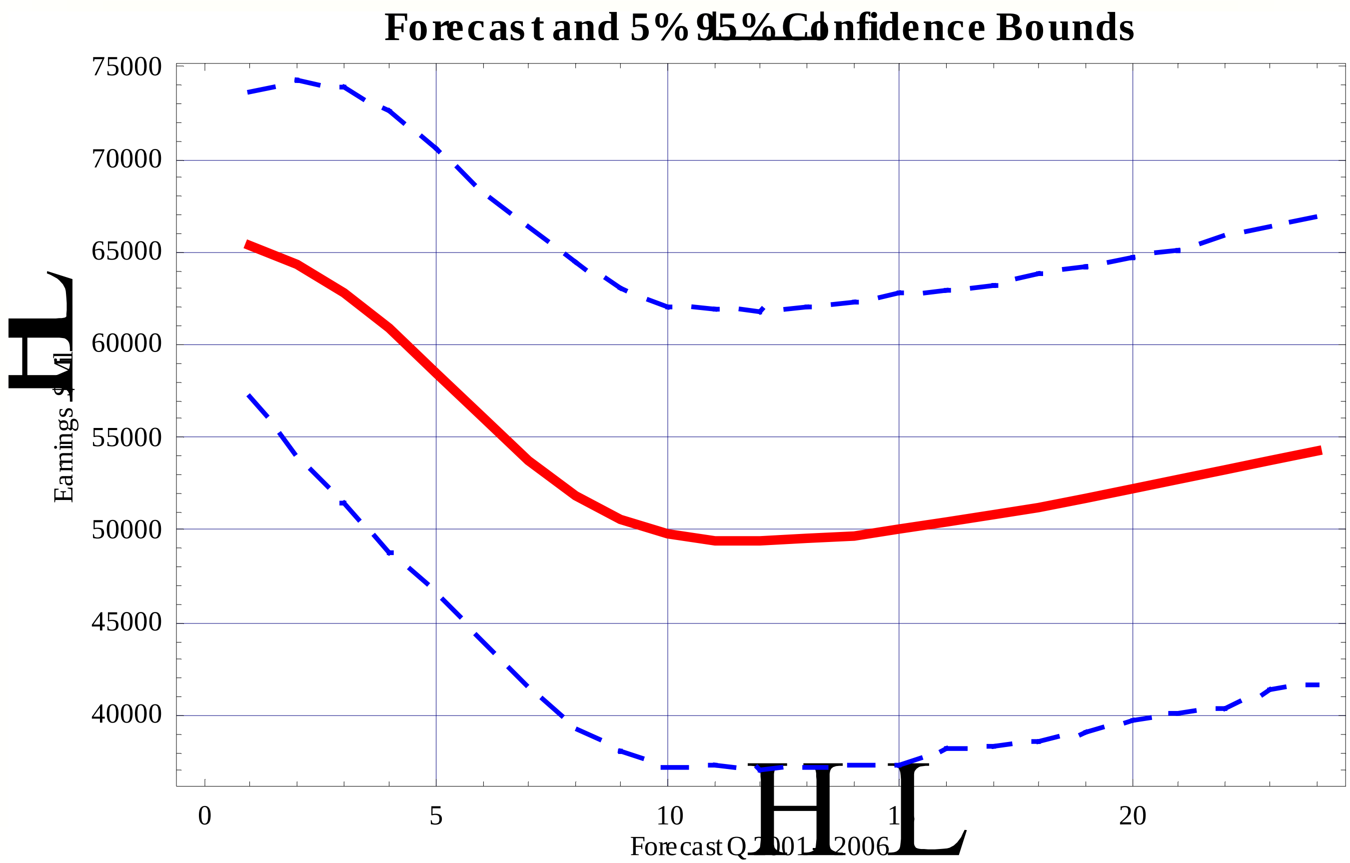
Baseline Forecast versus Simulated Alternatives



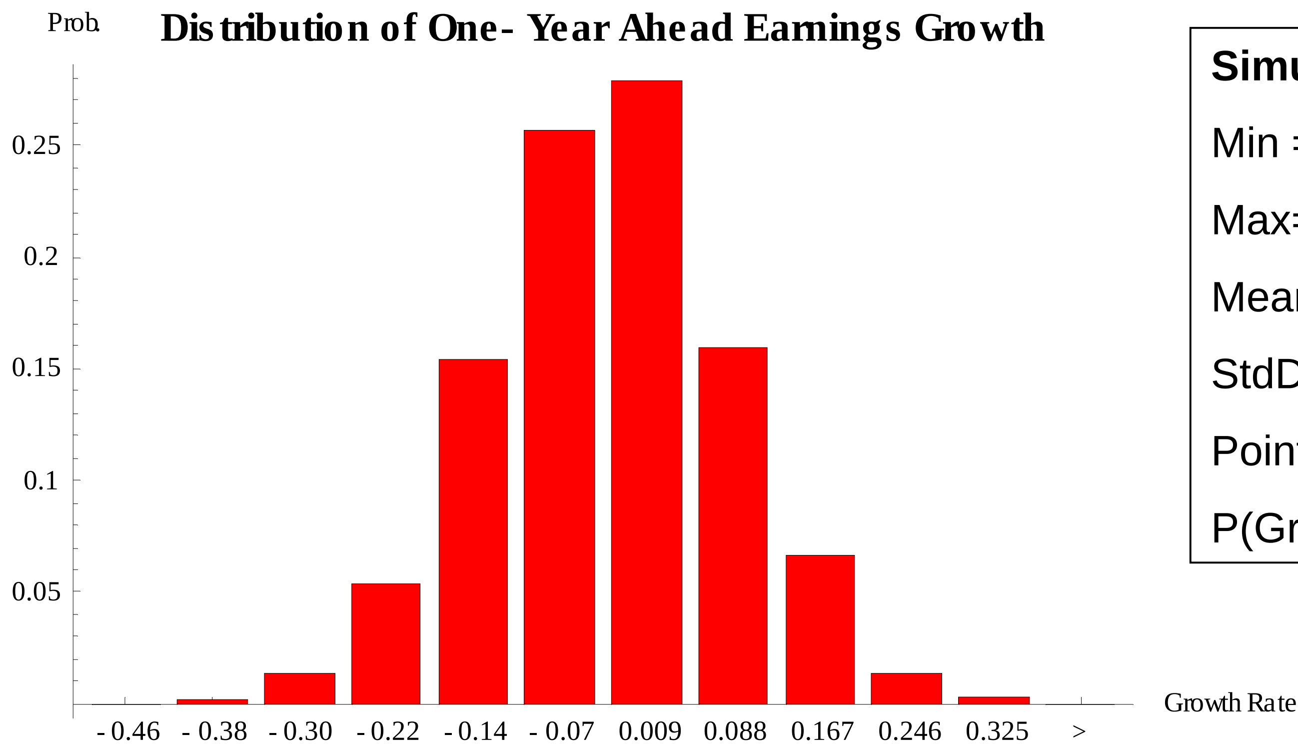
Simulation Statistics (5000 Trials)

	Forecast	Mean	Std Dev	5%-tile	95%-tile
1	65359.	65384.3	5021.96	57135.2	73658.7
2	64389.	64307.7	6151.84	54032.	74227.1
3	62788.1	62634.9	6830.92	51441.3	73852.
4	60907.9	60797.3	7136.51	48827.8	72557.6
5	58485.	58457.1	7342.35	46702.5	70633.8
6	55997.5	55963.9	7407.76	43952.4	68271.
7	53731.5	53745.9	7580.38	41502.9	66397.8
8	51822.7	51757.	7514.31	39342.9	64434.8
9	50549.7	50494.3	7513.33	38060.3	63022.7
10	49819.3	49810.	7551.5	37126.9	62029.2
11	49481.5	49524.6	7615.61	37319.8	61939.2
12	49404.8	49397.4	7502.42	37104.1	61831.7
13	49504.3	49590.6	7521.79	37140.8	62018.3
14	49727.9	49818.7	7545.89	37370.5	62282.4
15	50041.1	50211.3	7612.11	37344.2	62791.5
16	50448.5	50474.8	7572.55	38196.1	62882.6
17	50820.7	50795.9	7583.56	38299.4	63191.3
18	51249.	51300.1	7558.5	38608.7	63827.7
19	51734.8	51655.9	7604.35	39075.3	64230.6
20	52243.3	52218.1	7645.37	39709.5	64767.1
21	52780.5	52747.8	7602.68	40153.2	65081.3
22	53290.2	53261.7	7659.09	40385.4	65880.8
23	53787.6	53768.5	7602.23	41367.2	66366.3
24	54283.1	54328.8	7640.46	41683.8	66922.5

Simulation-based Confidence Bounds



Distribution of One-Year Ahead Earnings Growth



Simulation Statistics

Min = -46.6%

Max= 32.5%

Mean = -6.57%

StdDev = 11%

Point Forecast = -6.40

P(Gr>0) = 27%

Potential Applications

- **Equity**
  - **Assess and monitor sector risk**
  - **Stock selection and optimal portfolio construction**
  - **Return attribution**
- **Fixed Income**
  - **Quantify credit risk by industry and company**
  - **Track credit cycle**
  - **Distribution of extreme economic events**
- **Quantitative Risk Management**