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CFA Program

2024 CFA® PROGRAM CURRICULUM LEVEL III VOLUMES 1–6

CFA Institute®
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PORTFOLIO MANAGEMENT

CFA® Program Curriculum
2024 • LEVEL 3 • VOLUME 1

WILEY

ISBN 978-1-953337-61-0 (paper)
ISBN 978-1-953337-71-9 (ebook)
May 2023

Please visit our website at
www.WileyGlobalFinance.com.

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Please send any comments or feedback to info@cfainstitute.org, and we will review your suggestions carefully.

Portfolio Management

LEARNING MODULE

1

Capital Market Expectations, Part 1: Framework and Macro Considerations

by Christopher D. Piros, PhD, CFA (USA).

LEARNING OUTCOMES

Mastery	*The candidate should be able to:*
☐	discuss the role of, and a framework for, capital market expectations in the portfolio management process
☐	discuss challenges in developing capital market forecasts
☐	explain how exogenous shocks may affect economic growth trends
☐	discuss the application of economic growth trend analysis to the formulation of capital market expectations
☐	compare major approaches to economic forecasting
☐	discuss how business cycles affect short- and long-term expectations
☐	explain the relationship of inflation to the business cycle and the implications of inflation for cash, bonds, equity, and real estate returns
☐	discuss the effects of monetary and fiscal policy on business cycles
☐	interpret the shape of the yield curve as an economic predictor and discuss the relationship between the yield curve and fiscal and monetary policy
☐	identify and interpret macroeconomic, interest rate, and exchange rate linkages between economies

Parts of this reading have been adapted from a former Capital Market Expectations reading authored by John P. Calverley, Alan M. Meder, CPA, CFA, Brian D. Singer, CFA, and Renato Staub, PhD

1 INTRODUCTION & FRAMEWORK FOR DEVELOPING CAPITAL MARKET EXPECTATIONS

☐ discuss the role of, and a framework for, capital market expectations in the portfolio management process

A noted investment authority has written that the "fundamental law of investing is the uncertainty of the future."[1] Investors have no choice but to forecast elements of the future because nearly all investment decisions look toward it. Specifically, investment decisions incorporate the decision maker's expectations concerning factors and events believed to affect investment values. The decision maker integrates these views into expectations about the risk and return prospects of individual assets and groups of assets.

This reading's focus is **capital market expectations (CME)** expectations concerning the risk and return prospects of asset classes, however broadly or narrowly the investor defines those asset classes. Capital market expectations are an essential input to formulating a strategic asset allocation. For example, if an investor's investment policy statement specifies and defines eight permissible asset classes, the investor will need to have formulated long-term expectations concerning each of those asset classes. The investor may also act on short-term expectations. Insights into capital markets gleaned during CME setting should also help in formulating the expectations concerning individual assets that are needed in security selection and valuation.

This is the first of two readings on capital market expectations. A central theme of both readings is that a disciplined approach to setting expectations will be rewarded. With that in mind, Sections 1 and 2 of this reading present a general framework for developing capital market expectations and alert the reader to the range of problems and pitfalls that await investors and analysts in this arena. Sections 3–11 focus on the use of macroeconomic analysis in setting expectations. The second of the two CME readings builds on this foundation to address setting expectations for specific asset classes: equities, fixed income, real estate, and currencies. Various analytical tools are reviewed as needed throughout both readings.

Framework and Challenges

In this section, we provide a guide to collecting, organizing, combining, and interpreting investment information. After outlining the process, we turn to a discussion of typical problems and challenges to formulating the most informed judgments possible.

Before laying out the framework, we must be clear about what it needs to accomplish. The ultimate objective is to develop a set of projections with which to make informed investment decisions, specifically asset allocation decisions. As obvious as this goal may seem, it has important implications.

Asset allocation is the primary determinant of long-run portfolio performance.[2] The projections underlying these decisions are among the most important determinants of whether investors achieve their long-term goals. It thus follows that it is vital to get the long-run *level* of returns (approximately) right. Until the late 1990s, it was standard practice for institutional investors to extrapolate historical return

1 Peter L. Bernstein in the foreword to Rapaport and Mauboussin (2001), p. xiii.

2 See Brinson, Hood, and Beebower (1986) and Ibbotson and Kaplan (2000).

data into forecasts. At the height of the technology bubble,[3] this practice led many to project double-digit portfolio returns into the indefinite future. Such inflated projections allowed institutions to underfund their obligations and/or set unrealistic goals, many of which have had to be scaled back. Since that time, most institutions have adopted explicitly forward-looking methods of the type(s) discussed in our two CME readings, and return projections have declined sharply. Indeed, as of the beginning of 2018, consensus rate of return projections seemed to imply that US private foundations, which must distribute at least 5% of assets annually, could struggle to prudently generate long-run returns sufficient to cover their required distributions, their expenses, and inflation. To reiterate, projecting a realistic overall level of returns has to be a top priority.

As appealing as it is to think we could project asset returns with precision, that idea is unrealistic. Even the most sophisticated methods are likely to be subject to frustratingly large forecast errors over relevant horizons. We should, of course, seek to limit our forecast errors. We should not, however, put undue emphasis on the precision of projections for individual asset classes. Far more important objectives are to ensure internal consistency across asset classes (**cross-sectional consistency**) and over various time horizons (**intertemporal consistency**). This emphasis stems once again from the primary use of the projections—asset allocation decisions. Inconsistency across asset classes is likely to result in portfolios with poor risk–return characteristics over any horizon, whereas intertemporal inconsistency is likely to distort the connection between portfolio decisions and investment horizon.

Our discussion adopts the perspective of an analyst or team responsible for developing projections to be used by the firm's investment professionals in advising and/or managing portfolios for its clients. As the setting of explicit capital market expectations has become both more common and more sophisticated, many asset managers have adopted this centralized approach, enabling them to leverage the requisite expertise and deliver more consistent advice to all their clients.

A Framework for Developing Capital Market Expectations

The following is a framework for a disciplined approach to setting CME.

1. *Specify the set of expectations needed, including the time horizon(s) to which they apply.* This step requires the analyst to formulate an explicit list of the asset classes and investment horizon(s) for which projections are needed.
2. *Research the historical record.* Most forecasts have some connection to the past. For many markets, the historical record contains useful information on the asset's investment characteristics, suggesting at least some possible ranges for future results. Beyond the raw historical facts, the analyst should seek to identify and understand the factors that affect asset class returns.
3. *Specify the method(s) and/or model(s) to be used and their information requirements.* The analyst or team responsible for developing CME should be explicit about the method(s) and/or model(s) that will be used and should be able to justify the selection.
4. *Determine the best sources for information needs.* The analyst or team must identify those sources that provide the most accurate and timely information tailored to their needs.

3 Explosive growth of the internet in the late 1990s was accompanied by soaring valuations for virtually any internet-related investment. The NASDAQ composite index, which was very heavily weighted in technology stocks, nearly quintupled from 1997 to early 2000, then gave up all of those gains by mid-2002. A variety of names have been given to this episode including the tech or technology bubble.

5. *Interpret the current investment environment using the selected data and methods, applying experience and judgment.* Care should be taken to apply a common set of assumptions, compatible methodologies, and consistent judgments in order to ensure mutually consistent projections across asset classes and over time horizons.
6. *Provide the set of expectations needed, documenting conclusions.* The projections should be accompanied by the reasoning and assumptions behind them.
7. *Monitor actual outcomes and compare them with expectations, providing feedback to improve the expectations-setting process.* The most effective practice is likely to synchronize this step with the expectations-setting process, monitoring and reviewing outcomes on the same cycle as the projections are updated, although several cycles may be required to validate conclusions.

The first step in the CME framework requires the analyst to define the universe of asset classes for which she will develop expectations. The universe should include all of the asset classes that will typically be accorded a distinct allocation in client portfolios. To put it another way, the universe needs to reflect the key dimensions of decision making in the firm's investment process. On the other hand, the universe should be as small as possible because even pared down to minimum needs, the expectations-setting process can be quite challenging.

Steps 2 and 3 in the process involve understanding the historical performance of the asset classes and researching their return drivers. The information that needs to be collected mirrors considerations that defined the universe of assets in step 1. The more granular the classification of assets, the more granular the breakdown of information will need to be to support the investment process. Except in the simplest of cases, the analyst will need to slice the data in multiple dimensions. Among these are the following:

- Geography: global, regional, domestic versus non-domestic, economic blocs (e.g., the European Union), individual countries;
- Major asset classes: equity, fixed-income, real assets;
- Sub-asset classes:
  - Equities: styles, sizes, sectors, industries;
  - Fixed income: maturities, credit quality, securitization, fixed versus floating, nominal or inflation-protected;
  - Real assets: real estate, commodities, timber.

How each analyst approaches this task depends on the hierarchy of decisions in their investment process. One firm may prioritize segmenting the global equity market by Global Industry Classification Standard (GIC) sector, with geographic distinctions accorded secondary consideration, while another firm prioritizes decisions with respect to geography considering sector breakdowns as secondary.[4]

In Step 3, the analyst needs to be sensitive to the fact that both the effectiveness of forecasting approaches and relationships among variables are related to the investor's time horizon. As an example, a discounted cash flow approach to setting equity market expectations is usually considered to be most appropriate to long-range forecasting. If forecasts are also to be made for shorter, finite horizons, intertemporal consistency dictates that the method used for those projections must be calibrated so that its projections converge to the long-range forecast as the horizon extends.

4 There is extensive literature on the relative importance of country versus industry factors in global equity markets. Marcelo, Quiros, and Martins (2013) summarized the evidence as "vast and contradictory."

Executing the fourth step—determining the best information sources—requires researching the quality of alternative data sources and striving to fully understand the data. Using flawed or misunderstood data is a recipe for faulty analysis. Furthermore, analysts should be alert to new, superior data sources. Large, commercially available databases and reputable financial publications are likely the best avenue for obtaining widely disseminated information covering the broad spectrum of asset classes and geographies. Trade publications, academic studies, government and central bank reports, corporate filings, and broker/dealer and third-party research often provide more specialized information. Appropriate data frequencies must be selected. Daily series are of more use for setting shorter-term expectations. Monthly, quarterly, or annual data series are useful for setting longer-term CME.

The first four steps lay the foundation for the heart of the process: the fifth and sixth steps. Monitoring and interpreting the economic and market environment and assessing the implications for relevant investments are activities the analyst should be doing every day. In essence, step five could be labelled "implement your investment/research process" and step six could be labelled "at designated times, synthesize, document, and defend your views." Perhaps what most distinguishes these steps from the day-to-day investment process is that the analyst must make simultaneous projections for all asset classes and all designated, concrete horizons.

Finally, in step 7 we use experience to improve the expectations-setting process. We measure our previously formed expectations against actual results to assess the level of accuracy the process is delivering. Generally, good forecasts are:

- unbiased, objective, and well researched;
- efficient, in the sense of minimizing the size of forecast errors; and
- internally consistent, both cross-sectionally and intertemporally.

Although it is important to monitor outcomes for ways in which our forecasting process can be improved, our ability to assess the accuracy of our forecasts may be severely limited. A standard rule of thumb in statistics is that we need at least 30 observations to meaningfully test a hypothesis. Quantitative evaluation of forecast errors in real time may be of limited value in refining a process that is already reasonably well constructed (i.e., not subject to obvious gross errors). Hence, the most valuable part of the feedback loop will often be qualitative and judgmental.

EXAMPLE 1

Capital Market Expectations Setting: Information Requirements

1. Consider two investment strategists charged with developing capital market expectations for their firms, John Pearson and Michael Wu. Pearson works for a bank trust department that runs US balanced separately managed accounts (SMAs) for high-net-worth individuals. These accounts' mandates restrict investments to US equities, US investment-grade fixed-income instruments, and prime US money market instruments. The investment objective is long-term capital growth and income. In contrast, Wu works for

a large Hong Kong SAR–based, internationally focused asset manager that uses the following types of assets within its investment process:

Equities	Fixed Income	Alternative Investments
Asian equities Eurozone US large-cap US small-cap Canadian large-cap	Eurozone sovereign US government	Eastern European venture capital New Zealand timber US commercial real estate

Wu's firm runs SMAs with generally long-term time horizons and global tactical asset allocation (GTAA) programs. Compare and contrast the information and knowledge requirements of Pearson and Wu.

Guideline Answer:

Pearson's in-depth information requirements relate to US equity and fixed-income markets. By contrast, Wu's information requirements relate not only to US and non-US equity and fixed-income markets but also to three alternative investment types with non-public markets, located on three different continents. Wu has a more urgent need to be current on political, social, economic, and trading-oriented operational details worldwide than Pearson. Given their respective investment time horizons, Pearson's focus is on the long term whereas Wu needs to focus not only on the long term but also on near-term disequilibria among markets (for GTAA decisions). One challenge that Pearson has in US fixed-income markets that Wu does not face is the need to cover corporate and municipal as well as government debt securities. Nevertheless, Wu's overall information and knowledge requirements are clearly more demanding than Pearson's.

2 CHALLENGES IN FORECASTING

☐ discuss challenges in developing capital market forecasts

A range of problems can frustrate analysts' expectations-setting efforts. Expectations reflecting faulty analysis or assumptions may cause a portfolio manager to construct a portfolio that is inappropriate for the client. At the least, the portfolio manager may incur the costs of changing portfolio composition without any offsetting benefits. The following sections provide guidance on points that warrant special caution. The discussion focuses on problems in the use of data and on analyst mistakes and biases.

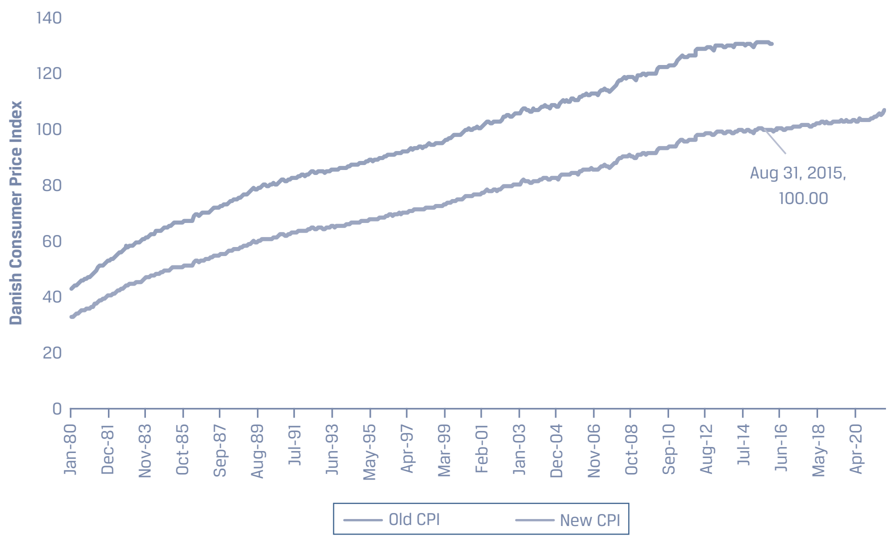
Limitations of Economic Data

The analyst needs to understand the definition, construction, timeliness, and accuracy of any data used, including any biases. The time lag with which economic data are collected, processed, and disseminated can impede their use because data that are not timely may be of little value in assessing current conditions. Some economic data may be reported with a lag as short as one week, whereas other important data may be reported with a lag of more than a quarter. The International Monetary Fund sometimes reports data for developing economies with a lag of two years or more. Older data increase the uncertainty concerning the current state of the economy with respect to that variable.

Furthermore, one or more official revisions to initial data values are common. Sometimes these revisions are substantial, which may give rise to significantly different inferences. Often only the most recent data point is revised. Other series are subject to periodic "benchmark revisions" that simultaneously revise all or a portion of the historical data series. In either case—routine updating of the most recent release or benchmark revision—the analyst must be aware that using revised data as if it were known at the time to which it applies often suggests strong historical relationships that are unreliable for forecasting.

Definitions and calculation methods change too. For example, the US Bureau of Labor Statistics (BLS) made significant changes to the Consumer Price Index for All Urban Consumers (CPI-U) in 1983 (treatment of owner-occupied housing) and again in 1991 (regression-based product quality adjustments). Analysts should also be aware that suppliers of economic and financial indexes periodically **re-base** these indexes, meaning that the specific period used as the base of the index is changed. Analysts should take care to avoid inadvertently mixing data relating to different base periods. Exhibit 1 illustrates the impact of re-basing a time series: Statistics Denmark announced that beginning January 2016, the Danish Consumer Price Index (CPI) was revised and the new base year is 2015. The CPI series based on the old base was no longer published, and the new series was computed back to 1980 retrospectively, such that the CPI took a value of 100.00 on 31 August 2015.

Exhibit 1: Danish CPI before and after Re-Basement (31 August 2015 = 100)



Sources: Statistics Denmark; Bloomberg

Data Measurement Errors and Biases

Analysts need to be aware of possible biases and/or errors in data series, including the following:

- Transcription errors. These are errors in gathering and recording data.

- Survivorship bias. This bias arises when a data series reflects only entities that survived to the end of the period. Without correction, statistics from such data can be misleading. Data on alternative assets such as hedge funds are notorious for survivorship bias.
- Appraisal (smoothed) data. For certain assets without liquid public markets, notably but not only real estate, appraisal data are used in lieu of transaction data. Appraised values tend to be less volatile than market-determined values. As a result, measured volatilities are biased downward and correlations with other assets tend to be understated.

The Limitations of Historical Estimates

Although history is often a helpful guide, the past should not be extrapolated uncritically. There are two primary issues with respect to using historical data. First, the data may not be representative of the future period for which an analyst needs to forecast. Second, even if the data are representative of the future, statistics calculated from that data may be poor estimates of the desired metrics. Both of these issues can be addressed to some extent by imposing structure (that is, a model) on how data is presumed to have been generated in the past and how it is expected to be generated in the future.

Changes in technological, political, legal, and regulatory environments; disruptions such as wars and other calamities; and changes in policy stances can all alter risk–return relationships. Such shifts are known as changes in **regime** (the governing set of relationships) and give rise to the statistical problem of **nonstationarity** (meaning, informally, that different parts of a data series reflect different underlying statistical properties). Statistical tools are available to help identify and model such changes or turning points.

A practical approach for an analyst to decide whether to use the whole of a long data series or only part of it involves answering two questions.

1. Is there any reason to believe that the entirety of the sample period is no longer relevant? In other words, has there been a fundamental regime change (such as political, economic, market, or asset class structure) during the sample period?
2. Do the data support the hypothesis that such a change has occurred?

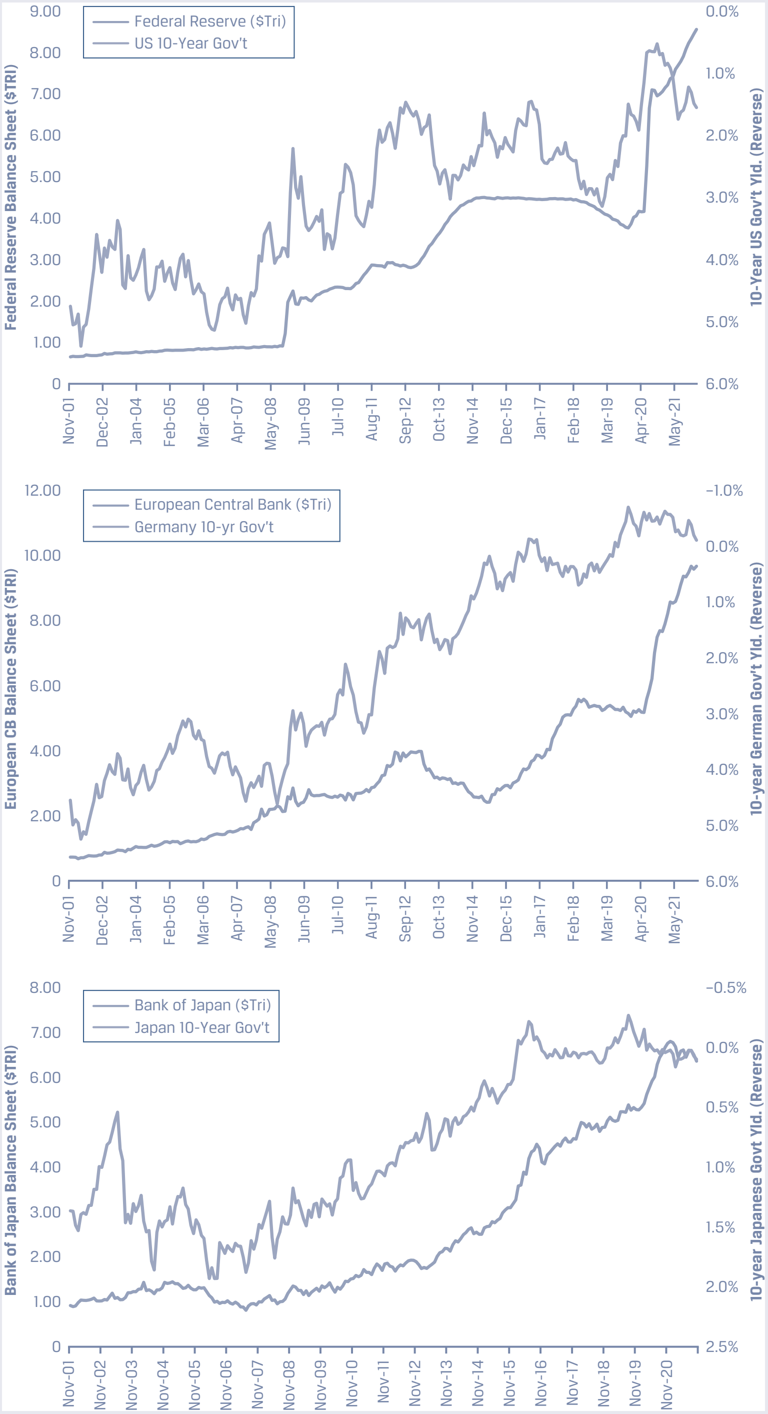
If the answer to both questions is yes, the analyst should use only that part of the time series that appears relevant to the present. Alternatively, he may apply statistical techniques that account for regime changes in the past data as well as the possibility of subsequent regime changes. Example 2 illustrates examples of changes in regime.

EXAMPLE 2

Regimes and the Relevance of Historical Bond Returns

In the 1970s, oil price shocks combined with accommodative monetary policy by the US Federal Reserve fueled sharply rising inflation. In 1980, the Fed abruptly shifted to an aggressively tight stance. After the initial shock of sharply higher interest rates, US bond yields trended downward for roughly 35 years as the Fed kept downward pressure on inflation. Throughout the 1980s and 1990s, the Fed eased monetary policy in the aftermath of the technology bubble. Then, switching to an extraordinarily expansionary policy in the midst of the 2008–2009 global financial crisis, the Fed reduced its policy rate to 0% in December 2008. Subsequently, it aggressively bought Treasury bonds and mortgage-backed securities. The Fed finally raised its policy rate target in December 2015 and continued hiking it up until it reached 2.5% at the end of 2018. In October 2017, it stopped rolling over maturing bonds, allowing its balance sheet to shrink, albeit very slowly. After the outbreak of COVID-19, the Fed once again cut its policy rate target, to 0%–0.25% in March 2020. It can be argued that bond returns from the 1970s through 2021 reflect at least three distinct regimes: the inflationary 1970s, with accommodative Fed policy; the 1980–2008 period of disinflationary policy and secularly falling yields; and the unprecedented 2009–21 period of zero interest rates and explosive liquidity provision. The years after the 2008-09 global financial crisis were dominated by multiple waves of central bank asset buying, not only in the United States but also globally. The most recent wave of asset purchases (quantitative easing, or QE) came after the outbreak of COVID-19. Exhibit 2 illustrates how QE by the Fed, the European Central Bank, and the Bank of Japan drove long-term government yields lower—even to negative territory in some cases.

Exhibit 2: Effects of QE on Long-Term Government Yield



Source: Bloomberg.

As of mid-2021, nominal interest rates were still negative in some developed markets, and major central banks including the Fed were aiming to "normalize" policy over the next few years. There is ample reason to believe that future bond returns will reflect a regime like none before.

In general, the analyst should use the longest data history for which there is reasonable assurance of stationarity. This guideline follows from the fact that sample statistics from a longer history are more precise than those with fewer observations.

Although it is tempting to assume that using higher-frequency data (e.g., monthly rather than annual observations) will also provide more-precise estimates, this assumption is not necessarily true. Although higher-frequency data improve the precision of sample variances, covariances, and correlations, they do *not* improve the precision of the sample mean.

When many variables are considered, a large number of observations may be a statistical necessity. For example, to calculate a sample covariance matrix, the number of observations must exceed the number of variables (assets). Otherwise, some asset combinations (i.e., portfolios) will spuriously appear to have zero volatility. This problem arises frequently in investment analysis, and a remedy is available. Covariance matrices are routinely estimated even for huge numbers of assets by assuming that returns are driven by a smaller set of common factors plus uncorrelated asset-specific components.

As the frequency of observations increases, the likelihood increases that data may be asynchronous (i.e., not simultaneous or concurrent in time) across variables. This means that data points for different variables may not reflect exactly the same period even though they are labeled as if they do. For example, daily data from different countries are typically asynchronous because of time zone differences. Asynchronicity can be a significant problem for daily, and perhaps even weekly data, because it distorts measured correlations and induces lead–lag relationships that might not exist if the data were measured synchronously. Lower-frequency data (e.g., monthly or quarterly) are less susceptible to asynchrony, although it can still arise. For example, two series that are released and labeled as monthly could reflect data collected at different times of the month.

As a final note on historical data, some care should be taken with respect to whether data are normally distributed. Historical asset returns, in particular, routinely exhibit skewness and "fat tails," which cause them to fail formal tests of normality. The cost in terms of analytical complexity of accounting for non-normality, however, can be quite high. As a practical matter, the added complexity is often not worth the cost.[5]

Ex Post Risk Can Be a Biased Measure of Ex Ante Risk

In interpreting historical prices and returns over a given sample period, the analyst needs to evaluate whether asset prices reflected the possibility of a very negative event that did not materialize during the period. This phenomenon is often referred to as the "peso problem." Looking backward, we are likely to underestimate *ex ante* risk and overestimate *ex ante* anticipated returns. The key point is that high *ex post* returns that reflect fears of adverse events that did not materialize provide a poor estimate of *ex ante* expected returns.

THE ARGENTINE PESO DEVALUATIONS

Starting in 1992, the Argentine peso (ARS) was pegged to the US dollar at a 1:1 ratio, and the ARS/USD exchange rate remained fixed at 1.0 until the Argentine great depression of 1998–2002, which was characterized by bank runs, riots, and sovereign debt default. In January 2002, the government decided to abandon the fixed exchange rate policy and devalued the peso to a rate of 1.4 ARS/USD. The currency was allowed to fluctuate freely, and the peso further depreciated to 3.8 ARS/USD by June 2001. Over the following years, additional default waves took place, and Argentina suffered from elevated inflation, fluctuating around

5 See Chapter 5 of Stewart, Piros, and Heisler (forthcoming 2019) for discussion of the effect of alternative probability distributions on asset allocation decisions.

20%–40%, with fiscal imbalances over the 2010s. The 2018 Argentine monetary crisis led to a further severe devaluation of the peso, trading at a rate of 18.6 ARS/USD at the end of 2017 but closing the year at 37.7.

The opposite situation is also a problem, especially for risk measures that consider only the subset of worst-case outcomes (e.g., value at risk, or VaR). If our data series includes even one observation of a rare event, we may substantially overstate the likelihood of such events happening in the future. Within a finite sample, the observed frequency of this bad outcome will far exceed its true probability. As a simple example, there were 22 trading days in March 2020, the month of the COVID-19-related market panic. On 16 March, the price of Facebook (now named as Meta Platforms) stock closed down –14.3%. The second worst day in the same month was 12 March, with the stock price down –9.3%. Based on this sample, the (interpolated) daily 5% VaR on Facebook stock was 13.4%. That is, an investor in Facebook shares would expect to lose at least 13.4% once every 20 days. Note that the stock did not experience any such loss over the subsequent 19 months.

Biases in Analysts' Methods

Analysts naturally search for relationships that will help in developing better capital market expectations. Among the preventable biases that the analyst may introduce are the following:

- Data-mining bias arises from repeatedly searching a dataset until a statistically significant pattern emerges. It is almost inevitable that some relationship will appear. Such patterns cannot be expected to have predictive value. Lack of an explicit economic rationale for a variable's usefulness is a warning sign of a data-mining problem: no story, no future.[6] Of course, the analyst must be wary of inventing the story after discovering the relationship and bear in mind that correlation does not imply causation.
- Time-period bias relates to results that are period specific. Research findings often turn out to be sensitive to the selection of specific starting and/or ending dates.

SMALL-CAP OUTPERFORMANCE AND TIME-PERIOD BIAS

Evidence suggesting that small-cap stocks outperform large-cap stocks over time (the so-called small firm effect) is very sensitive to the choice of sample period. From 1926 through 1974, US small-cap stocks outperformed large caps by 0.43% per year, but if we skip the Great Depression and start in 1932, the differential becomes 3.49% per year. Similarly, small caps outperformed by 4.5% per year from 2000 through 2010 but underperformed by –2.8% per year from 2010 through 2020.[7]

How might analysts avoid using an irrelevant variable in a forecasting model? The analyst should scrutinize the variable selection process for data-mining bias and be able to provide an economic rationale for the variable's usefulness in a forecasting model. A further practical check is to examine the forecasting relationship out of sample (i.e., on data that was not used to estimate the relationship).

6 See McQueen and Thorley (1999).

7 Source: Ibbotson Associates database (Morningstar). Returns calculated by the author.

The Failure to Account for Conditioning Information

The discussion of regimes introduced the notion that assets' risk and return characteristics vary with the economic and market environment. That fact explains why economic analysis is important in expectation setting. The analyst should not ignore relevant information or analysis in formulating expectations. Unconditional forecasts, which dilute this information by averaging over environments, can lead to misperception of prospective risk and return. Example 3 illustrates how an analyst may use conditioning information.

EXAMPLE 3

Incorporating Conditioning Information

Noah Sota uses the CAPM to set capital market expectations. He estimates that one asset class has a beta of 0.8 in economic expansions and 1.2 in recessions. The expected return on the market is 12% in an expansion and 4% in a recession. The risk-free rate is assumed to be constant at 2%. Expansion and recession are equally likely. Sota aims to calculate the unconditional expected return for the asset class.

The conditional expected returns on the asset are 10% = 2% + 0.8 × (12% − 2%) in an expansion and 4.4% = 2% + 1.2 × (4% − 2%) in a recession. Weighting by the probabilities of expansion and recession, the unconditional expected return is 7.2% = [(0.5 × 10%) + (0.5 × 4.4%)].

EXAMPLE 4

Ignoring Conditioning Information

1. Following on from the scenario in Example 3, one of Noah Sota's colleagues suggests an alternative approach to calculate the unconditional expected return for the asset class. His method is to calculate the unconditional beta to be used in the CAPM formula, 1.0 = (0.5 × 0.8) + (0.5 × 1.2). He then works out the unconditional expected return on the market portfolio, 8% = (0.5 × 12%) + (0.5 × 4%). Finally, using the unconditional beta and the unconditional market return, he calculates the unconditional expected return on the asset class as 8.0% = 2.0% + 1.0 × (8% − 2%).

   Explain why the alternative approach is right or wrong.

   Guideline Answer:

   The approach suggested by Sota's colleague is wrong. It ignores the fact that the market excess return and the asset's beta vary with the business cycle. The expected return of 8% calculated this way would overestimate the (unconditional) expected return on this asset class. Such a return forecast would ignore the fact that the beta differs for expansion (0.8) and recession (1.2).

Misinterpretation of Correlations

When a variable *A* is found to be significantly correlated with another variable *B*, there are at least four possible explanations: (1) A predicts B, (2) B predicts A, (3) a third variable C predicts both A and B, or (4) the relationship is spurious. The observed correlation alone does not allow us to distinguish among these situations. Consequently, correlation relationships should not be used in a predictive model without investigating the underlying linkages.

Although apparently significant correlations can be spurious, it is also true that lack of a strong correlation can be misleading. A negligible measured correlation may reflect a strong but *nonlinear* relationship. Analysts should explore this possibility if they have a solid reason for believing a relationship exists.

Psychological Biases

The behavioral finance literature documents a long and growing list of psychological biases that can affect investment decisions. Only a few of the more prominent ones that could undermine the analyst's ability to make accurate and unbiased forecasts are outlined here. Furthermore, note that the literature contains various names and definitions of behavioral biases, which are not necessarily mutually exclusive.

- Anchoring bias is the tendency to give disproportionate weight to the first information received or first number envisioned, which is then adjusted. Such adjustment is often insufficient, and approximations are consequently biased. Analysts can try to avoid anchoring bias by consciously attempting to avoid premature conclusions.
- Status quo bias reflects the tendency for forecasts to perpetuate recent observations—that is, to avoid making changes and preserve the status quo, and/or to accept a default option. This bias may reflect greater pain from errors of commission (making a change) than from errors of omission (doing nothing). Status quo bias can be mitigated by disciplined effort to avoid "anchoring" on the status quo.
- Confirmation bias is the tendency to seek and overweight evidence or information that confirms one's existing or preferred beliefs and to discount evidence that contradicts those beliefs. This bias can be mitigated by examining all evidence with equal rigor and/or debating with a knowledgeable person capable of arguing against one's own views.
- Overconfidence bias is unwarranted confidence in one's own intuitive reasoning, judgment, knowledge, and/or ability. This bias may lead an analyst to overestimate the accuracy of her forecasts and/or fail to consider a sufficiently broad range of possible outcomes or scenarios. Analysts may not only fail to fully account for uncertainty about which they are aware (sometimes described as "known unknowns") but they also are very likely to ignore the possibility of uncertainties about which they are not even aware (sometimes described as "unknown unknowns").
- Prudence bias reflects the tendency to temper forecasts so that they do not appear extreme or the tendency to be overly cautious in forecasting. In decision-making contexts, one may be too cautious when making decisions that could damage one's career or reputation. This bias can be mitigated by conscious effort to identify plausible scenarios that would give rise to more extreme outcomes and to give greater weight to such scenarios in the forecast.

- Availability bias is the tendency to be overly influenced by events that have left a strong impression and/or for which it is easy to recall an example. Recent events may likewise be overemphasized. The effect of this bias can be mitigated by attempting to base conclusions on objective evidence and analytical procedures.

EXAMPLE 5

Biases in Forecasting and Decision Making

1. Cynthia Casey is a London-based investment adviser with a clientele of ultra-high-net-worth individuals in the UK, the US, and the EU. Within the equity portion of her portfolios, she rarely deviates significantly from the country weightings of the MSCI World Index, even though more often than not she tilts the allocation in the right direction. Hence, she can claim a good tactical track record despite having added little value in terms of return through tactical allocation. Because most investors have an implicit "home bias," her European clients tend to view their portfolios as significantly overweight the US (nearly 50% of the World index) and are happy because the US market outperformed the MSCI World ex-US Index by about 8% per year over the 10 years ending 31 December 2020. Conversely, her US clients are unhappy because Casey persistently projected US outperformance but maintained what they instinctively perceive as a significant underweight in the United States. Citing year-to-date performance as of 31 December 2020—US performance was up 21%, while World ex-US performance was up 8%, largely lagging behind the United States, with 8 of 15 European markets actually down in local currencies—Casey's US clients are pressuring her to aggressively increase allocations to US equities. Although experience has taught her to be wary of chasing a strong market, Casey vividly remembers losing clients in the late 1990s because she doubted that the explosive rally in technology stocks would be sustained. With that in mind, she has looked for and found a rationale for a bullish view on US stocks—very robust year-to-date earnings growth.

   What psychological biases are Casey and her clients exhibiting?

   Guideline Answer:

   Casey's clients are implicitly anchoring their expectations on the performance of their respective domestic markets. In pressing Casey to increase the allocation to US stocks based on recent outperformance, her US clients are clearly projecting continuation of the trend, a status quo bias. Casey herself is exhibiting several biases. Prudence bias is apparent in the fact that she has a good record of projecting the correct direction of relative performance among markets but has not translated that into reallocations large enough to add meaningful value. We cannot assess whether that bias affects the magnitude of her forecasts, the extent to which she responds to the opportunities, or both. Losing clients when she doubted the sustainability of the late 1990s technology rally made a very strong impression on Casey, so much so that she has apparently convinced herself to look for a reason to believe the recent relative performance trends will persist. This is indicative of availability bias. Searching for evidence to support a favored view (continued strength of the US market) is a clear sign of confirmation bias, whereas finding support for that view in the recent strength of earnings growth reflects status quo bias.

Model Uncertainty

The analyst usually encounters at least three kinds of uncertainty in conducting an analysis. **Model uncertainty** pertains to whether a selected model is structurally and/or conceptually correct. **Parameter uncertainty** arises because a quantitative model's parameters are invariably estimated with error. **Input uncertainty** concerns whether the inputs are correct. Any or all of these may give rise to erroneous forecasts and/or cause the unwary analyst to overestimate the accuracy and reliability of his forecasts.

The effects of parameter uncertainty can be mitigated through due attention to estimation errors. Input uncertainty arises primarily from the need to proxy for an unobservable variable such as "the market portfolio" in the CAPM. Whether or not this is a serious issue depends on the context. It is a problem if the analyst wants to test the validity of the underlying theory or identify "anomalies" relative to the model. It is less of an issue if the analyst is merely focused on useful empirical relationships rather than proof of concept/theory. Model uncertainty is potentially the most serious issue because the wrong model may lead an analyst to fundamentally flawed conclusions.

Our discussion of the limitations of historical data touched on a model that led many investors far astray in the late 1990s. Up to that point, the implicit model used by many, if not most, institutional investors for setting long-term equity expectations was, "The *ex ante* expected return is, was, and always will be a constant number μ, and the best estimate of that number is the mean over the longest sample available." As the market soared in the late 1990s, the historical estimate of μ rose steadily, leading investors to shift more heavily into equities, which fueled further price appreciation and more reallocation toward equities, and so on, until the technology bubble burst. Ironically, belief in the sanctity of historical estimates coincided with the diametrically opposed notion that the "new economy" made historical economic and market relationships obsolete. There seemed to be no limits to growth or to valuations, at least in some segments of the market. But, of course, there were. This description of the technology bubble illustrates the breakdown of a particular forecasting model. It is not a literal description of anyone's thought process. For various reasons, however—competitive pressures, status quo/availability/prudence biases—many investors acted *as if* they were following the model.

Another flawed model unraveled during the global financial crisis of 2007–2009. One component of that model was the notion that housing price declines are geographically isolated events: There was no risk of a nationwide housing slump. A second component involved "originate to sell" loan pipelines: businesses that made loans with the intention of immediately selling them to investors and therefore had very little incentive to vet loan quality. A third component was the notion that the macro risk of an ever-growing supply of increasingly poor-quality mortgages could be diversified away by progressive layers of securitization. End investors were implicitly sold the notion that the securities were low risk because numerous computer simulations showed that the "micro" risk of individual loans was well diversified. The macro risk of a housing crisis, however, was not reflected in prices and yields—until, of course, the model proved to be flawed. The scenario highlighted here provides another illustration of a particular model breaking down. In this case, it was a flawed model of risk and diversification, and its breakdown was one of many aspects of the financial crisis.