

Cognitive Biases in Market Forecasts

The frailty of forecasting.

Kenneth L. Fisher and Meir Statman

Some days it seems as if the world is divided into two groups, those who forecast that the DJIA will soar to 36,000 very soon and those who forecast, with equal confidence, that it will plummet to 3,600. We argue that forecasters often exaggerate the reliability of their forecasts, and trace this exaggeration to the illusion of validity.

“People are prone to experience much confidence in highly fallible judgment, a phenomenon that may be termed the *illusion of validity*,” write Kahneman and Tversky [1973]. “Like other perceptual and judgmental errors, the illusion of validity persists even when its illusionary character is recognized” (p. 249).

We discuss five cognitive biases that underlie the illusion of validity: overconfidence, confirmation, representativeness, anchoring, and hindsight. We use forecasts based on P/E ratios and dividend yields to illustrate the biases and offer remedies.

P/E RATIOS, DIVIDEND YIELDS, AND FUTURE RETURNS

The returns of 1980 will warm the hearts of those who believe that low P/E ratios forecast imminent high returns, but the returns of 1918 will break their hearts. The P/E ratio stood at a low 7.5 at the beginning of January 1980, and the S&P 500 index was up a healthy 32.42% for the year. But the P/E ratio stood at an even lower 6.3 at the beginning of January 1917, and stocks were *down* 15.09% for the year. Similarly, while the high

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EXHIBIT 1A
RELATIONSHIP BETWEEN P/E RATIOS AT
BEGINNING OF A YEAR AND STOCK RETURNS
OVER FOLLOWING YEAR—1872–1999

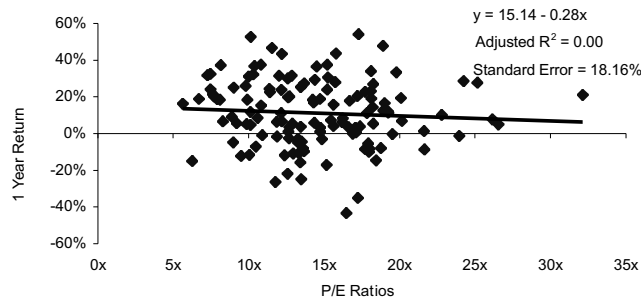


EXHIBIT 1B
RELATIONSHIP BETWEEN P/E RATIOS AT
BEGINNING OF A YEAR AND STOCK RETURNS
OVER FOLLOWING TWO (NON-OVERLAPPING)
YEARS—1872–1999

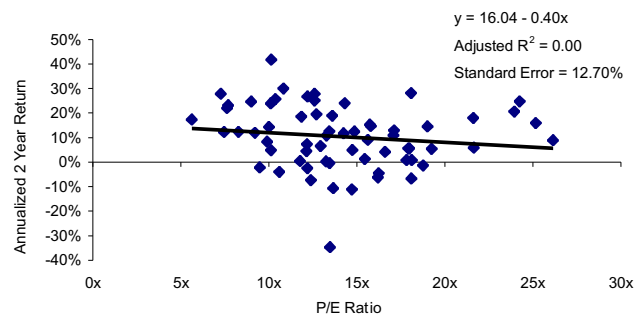


EXHIBIT 2A
RELATIONSHIP BETWEEN DIVIDEND YIELD AT
BEGINNING OF A YEAR AND STOCK RETURNS
OVER FOLLOWING YEAR—1872–1999

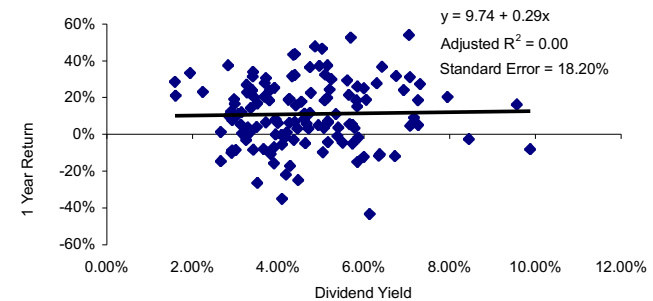
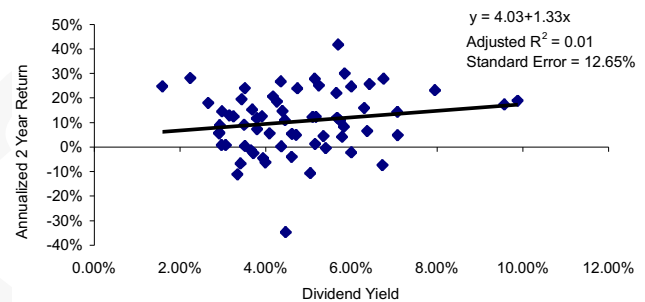


EXHIBIT 2B
RELATIONSHIP BETWEEN DIVIDEND YIELD AT
BEGINNING OF A YEAR AND ANNUALIZED
STOCK RETURNS OVER FOLLOWING TWO
(NON-OVERLAPPING) YEARS—1872–1999



24.0 P/E ratio of 1934 was followed by a 1.44% loss, the even higher 25.8 P/E ratio of 1922 was followed by a 27.65% gain.

We study the P/E ratios and dividend yields at the beginning of the 128 years from 1872 through 1999, and find that they provide unreliable forecasts of future returns. (The sources of the data are described in the appendix.) As can be seen in Exhibits 1A and 1B, there is no statistically significant relationship between P/E ratios at the beginning of a year and returns during the following year or during the following two (non-overlapping) years. As can be seen in Exhibits 2A and 2B, there is no statistically significant relationship between dividend yields at the beginning of a year and returns during the following year or during the following two (non-overlapping) years. The results are similar when real returns replace nominal returns.

P/E ratios and dividend yields provide more reliable forecasts over longer periods. We discuss ten-year periods later.

Many investors are especially concerned about the short-horizon implications of very high P/E ratios, fearing that they forecast imminent disastrous returns. Yet history offers little support for such fear. For example, P/E ratios over 19 have never been followed by losses greater than 10% during the following year. While high P/E ratios can surely be followed soon by disastrous returns, it is ironic that investors believe that such returns are the common feature of stock market history.

As can be seen in Exhibit 3A, the six highest P/E ratios, ranging from 32.2 at the beginning of 1999 to 24.0 at the beginning of 1934, are were much higher than the 13.6 median P/E ratio. Yet the *lowest* return in a year following these six highest P/E ratios was a 1.44%

EXHIBIT 3A
ONE-YEAR RETURNS FOLLOWING
SIX HIGHEST P/E RATIOS

Year	P/E Ratio at Beginning of Year	Stock Returns During Year
1999	32.2	21.03%
1895	26.6	4.92%
1992	26.2	7.67%
1922	25.8	27.65%
1998	24.3	28.58%
1934	24.0	-1.44%

EXHIBIT 3B
LOWEST ONE-YEAR STOCK RETURNS
AND CORRESPONDING P/E RATIOS
AT BEGINNING OF YEAR

Year	P/E Ratio at Beginning of Year	Stock Returns During Year
1931	16.5	-43.34%
1937	17.2	-35.03%
1974	11.8	-26.47%
1930	13.5	-24.90%
1877	12.7	-16.88%
1973	18.4	-14.66%

loss in 1934. Indeed, the lowest returns have followed middling P/E ratios, not very high ones (Exhibit 3B). The lowest annual return, a 43.34% loss of 1931, followed a 16.5 P/E ratio. Similarly, the 26.47% loss of 1974 followed an 11.8 P/E ratio.

OVERCONFIDENCE

Overconfidence is one of the cognitive biases that underlie the illusion of validity. To understand the overconfidence bias, imagine that you are asked to estimate the typical gestation period of the Asian elephant. In particular, you are asked to provide two guesses of the gestation period—a low guess and a high one—such that you are 90% confident that the right answer lies between the two.

Most people know, with justified confidence, that the average gestation period of humans is approximately nine months. So a 90% confidence interval ranging from a low of 8.5 months to a high of 9.5 months is well calibrated, not overconfident; there is at least a 90% chance that the true average gestation period of humans falls between the low and high guesses.

The average gestation period for an Asian elephant is approximately 21 months, and zoologists would not be overconfident if they were to provide an equally narrow 90% confidence interval around that number. But the rest of us should be mindful of overconfidence. We can avoid overconfidence by providing confidence intervals consistent with our knowledge, perhaps a low of 3 months and a high of 40.

Now imagine a set of ten questions similar to the one about the Asian elephant (e.g., what is the weight of a Boeing 747 airplane?). On average, one true answer of the ten will be higher than the high guess or lower than the low guess if people calibrate their 90% confidence level properly. But people are overconfident; on average, more than one in ten fall outside the 90% confidence interval.

Regression analysis is a good remedy for overconfidence. The scatter diagrams of the regressions in Exhibits 1A and 1B provide visual images of the right level of confidence in P/E-based forecasts of returns. We can see that the dots are scattered all over the place, so one should not place much confidence in P/E ratios as precise predictors of returns. Summary statistics, such as the R^2 and standard errors, convert visual images into numbers. The standard error of the regression of one-year returns on P/E is 18.16%. This standard error implies, for example, that while the expected return for a P/E ratio of 20 is 9.54%, the 90% confidence interval for a return forecast extends from a 20.33% loss to a 39.41% gain. (The 90% confidence interval extends from 1.645 standard deviations (i.e., 29.87%) below the expected return of 9.54% to 1.645 standard deviations above it.)

Well-calibrated P/E-based forecasts have wide bounds. Such well-calibrated forecasts are likely to portray forecasters as timid. But bolder forecasters might be overconfident.

CONFIRMATION

Einhorn and Hogarth [1978] argue that the illusion of validity persists because people fall prey to the confirmation bias; they focus on information that is consistent with their beliefs while neglecting inconsistent information. As Robert Park, a physicist, said in an interview with William Broad about faulty research on electromagnetic fields:

It's often not deliberate fraud.... People are awfully good at fooling themselves. They're so sure they know the answer that they don't want to confuse people with ugly-looking data [1999, p. A1].

We can overcome the confirmation bias by examining all data, confirming as well as disconfirming. Consider, in particular, an examination of the hypothesis that low dividend yields forecast low returns while high dividend yields forecast high returns. Define dividend yields as high if they exceed their median over the 128 years from 1872 through 1999 and as low if they fall below it. The median dividend yield for the period was 4.43%. Define one-year returns as high and low in a similar fashion. The median return was 10.50%. Exhibit 4A presents a schematic view of the frequency of observations in the four cells of a matrix.

The first cell includes observations where dividend yields were low and subsequent returns were low. These are *positive hits*. The fourth cell has observations where dividend yields were high and subsequent returns were also high. These are *negative hits*. Positive hits and negative hits are confirming evidence, observations consistent with the hypothesis that low dividend yields forecast low returns and high dividend yields forecast high returns.

The other two cells have disconfirming evidence. That is, the second cell includes *false positive* observations where dividend yields were low but subsequent returns were high, and the third cell is the *false negatives*, observations where dividend yields were high but subsequent returns were low. False positives and false negatives are disconfirming evidence.

Correct analysis of the hypothesis requires examination of all four cells. Those who examine only the positive and negative hits fall prey to the confirmation bias.

The confirmation bias is common. Consider, for example, Prechter's discussion of low dividend yield as a forecaster of low returns:

August 1987 saw a historically high valuation of dividends, beating out even that of 1929. The result was a 1,000 point crash [1997, p. 110].

**EXHIBIT 4A
RELATIONSHIP BETWEEN DIVIDEND YIELDS
AND FUTURE RETURNS**

	Below-Median Return	Above-Median Return
Below-Median Dividend Yield	Positive hit	False positive
Above-Median Dividend Yield	False negative	Negative hit

**EXHIBIT 4B
RELATIONSHIP BETWEEN DIVIDEND YIELDS
AT BEGINNING OF A YEAR AND STOCK
RETURNS OVER FOLLOWING YEAR 1872-1999**

	Below-Median Return	Above-Median Return	Total
Below-Median Dividend Yield	33	31	64
Above-Median Dividend Yield	31	33	64
Total	64	64	128

Chi-square = 0.03.

**EXHIBIT 4C
RELATIONSHIP BETWEEN DIVIDEND YIELDS
AT BEGINNING OF YEAR AND STOCK RETURNS
OVER FOLLOWING (NON-OVERLAPPING)
TWO YEARS 1872-1999**

	Below-Median Return	Above-Median Return	Total
Below-Median Dividend Yield	17	15	32
Above-Median Dividend Yield	15	17	32
Total	32	32	64

Chi-square = 0.06.

Critical chi-square for 5% level of significance is 3.841.

Median dividend yield over 128 years 1872-1999 is 4.43%. Median return during a year is 10.50%.

**EXHIBIT 5A
RELATIONSHIP BETWEEN P/E RATIOS
AND FUTURE RETURNS**

	Below-Median Return	Above-Median Return
Above-Median P/E Ratios	Positive hit	False positive
Below-Median P/E Ratios	False negative	Negative hit

**EXHIBIT 5B
RELATIONSHIP BETWEEN P/E RATIOS AT
BEGINNING OF A YEAR AND STOCK RETURNS
OVER FOLLOWING YEAR 1872-1999**

	Below-Median Return	Above-Median Return	Total
Above-Median P/E Ratios	32	32	64
Below-Median P/E Ratios	32	32	64
Total	64	64	128

Chi-square = 0.00.

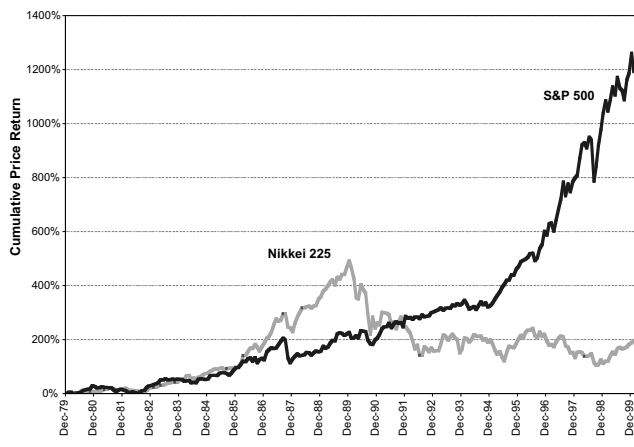
**EXHIBIT 5C
RELATIONSHIP BETWEEN P/E RATIOS AT
BEGINNING OF YEAR AND STOCK RETURNS
OVER FOLLOWING (NON-OVERLAPPING)
TWO YEARS 1872-1999**

	Below-Median Return	Above-Median Return	Total
Above-Median P/E Ratios	19	13	32
Below-Median P/E Ratios	13	19	32
Total	32	32	64

Chi-square = 1.56.

Median P/E ratio over 128 years 1872-1999 is 13.6X. Median return during a year is 10.50%.

EXHIBIT 6
S&P 500 VERSUS NIKKEI 225
DECEMBER 1979–1999



Prechter’s observation is a positive hit, an observation consistent with the hypothesis that low dividend yields (i.e., “high valuation of dividends”) forecast low returns. But we need an account of false positives and false negatives as well.

Consider dividend yields as forecasters of one-year returns. It turns out, as presented in Exhibit 4B, that there are 33 positive hits in the first cell and 33 negative hits in the fourth. These are consistent with the hypothesis that low dividend yields forecast low returns, while high dividend yields forecast high returns. But the evidence against the hypothesis is almost as strong as the evidence for it; there are 31 false positives in the second cell and 31 false negatives in the third.

The deviations of actual observations from those expected by chance alone are too small to be statistically significant. We can conclude only that dividend yields enable no statistically significant forecasts of returns in the following year. We also find no statistically significant relationship between dividend yields and returns in the following (non-overlapping) two-year returns, as depicted in Exhibit 4C.

The same is true for the relationship between P/E ratios and returns during the following year or during the following two (non-overlapping) years, as depicted in Exhibits 5A, 5B, and 5C. For example, while high P/E ratios were followed by low returns in 32 years, high P/E ratios were followed by high returns in an equal 32 years.

Low dividend yields are followed almost equally by low returns and high returns, and high dividend yields are followed almost equally by high returns and low returns. The same is true for high and low P/E ratios. Thus, dividend yields and P/E ratios are unreliable fore-

casters of future returns because they provide so many bad forecasts along with the good ones.

REPRESENTATIVENESS

Like the narrator in a Greek drama, Yutaka Yamaguchi, deputy governor of Japan’s central bank, took the lectern here and sadly described how the booming Japanese economy in the late 1980s came to tragedy. His description of Japan at its peak sounded eerily parallel to America’s in today’s still evolving boom (Uchitelle [1999, p. C23]).

Exhibit 6 displays the returns in the Japanese stock market of the 1980s and the U.S. stock market of the 1990s. There are surely similarities between the two, but over-reliance on similarity can trigger a representativeness bias.

To understand the representativeness bias, consider an experiment by Kahneman and Tversky [1973]. Subjects were given a description of “Jack,” and told he was drawn at random from a population of lawyers and engineers. Subjects were then asked to indicate the probability that Jack is an engineer:

Jack is a 45-year-old man. He is married and has four children. He is generally conservative, careful and ambitious. He shows no interest in political and social issues and spends most of his time on his many hobbies, which include home carpentry, sailing, and mathematical puzzles.

One group of subjects is told that the population includes 30 engineers and 70 lawyers. The other group is told that the population includes 70 engineers and 30 lawyers. Kahneman and Tversky found that their subjects fell prey to the representative bias; they focused on “singular” data, namely, the similarity between Jack and the stereotype of an engineer, and disregarded “base rate” data, namely, the proportion of engineers and lawyers in the population.

The actual probability that Jack is an engineer, given that the population includes 70 engineers, is significantly higher than the probability that he is an engineer, given that the population includes only 30 engineers. Yet Kahneman and Tversky’s respondents answered as if there were no significant differences between the estimates of the probability that Jack is an engineer in the two different versions of the story. In essence, the subjects focused

entirely on Jack's "representativeness"—the similarity between Jack and the stereotype of an engineer. They ignored everything else.

The representativeness bias might underlie the conclusion that some similar features in the Japanese market of the 1980s and the U.S. market of the 1990s presage a decline in the U.S. market. Yet the finding that the relationship between dividend yields and P/E ratios and subsequent returns is weak constitutes base rate information, information that must be considered alongside singular similarity data.

ANCHORING

The Ford Foundation was concerned in 1969 that colleges and foundations were allocating very little to stocks. In "Managing Education Endowment," the foundation traced that phenomenon to a cognitive bias, born of the 1929 crash:

It is our conclusion that the past thinking by many endowment managers has been overly influenced by fear of a major crash. Although nobody can ever be certain what the future may bring, we do not think a long-term policy founded on such fear can survive dispassionate analysis of the probability of a crash and the long-term cost of guarding against one [1969, p. 14].

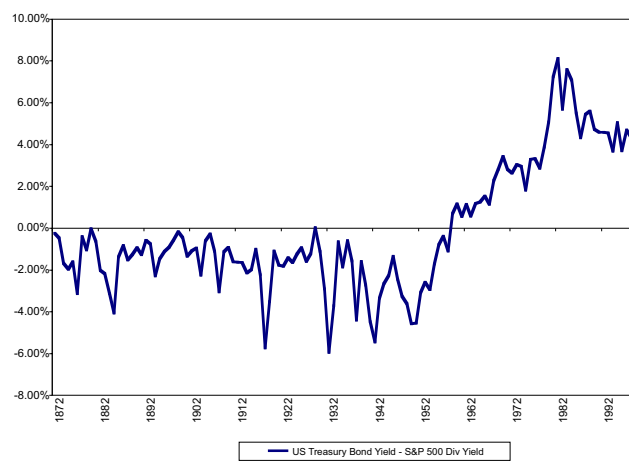
The cognitive bias that the Ford Foundation noted is the *anchoring* bias. Tversky and Kahneman [1974] demonstrated the anchoring bias in experiments, such as a United Nations experiment.

Subjects watched as a number between 0 and 100 was drawn from a spinning wheel of fortune. Imagine that the number is 10. Next, subjects were asked if they thought that the percentage of African nations in the United Nations is higher or lower than 10. Last, subjects were asked for their estimates of the percentage of African nations in the United Nations.

Tversky and Kahneman found, for example, that the median estimate of the percentage of African countries in the United Nations was 25 for subjects whose wheel of fortune spin landed on 10, but the median estimate was 45 for subjects whose spin landed on 65.

The anchoring bias involves the tendency to anchor estimates to salient numbers even if these numbers have little or no relevance to the estimates. The Ford Foundation, for example, argued that the market forecasts

EXHIBIT 7
DIFFERENCE BETWEEN BOND YIELDS
AND DIVIDEND YIELDS—1872–1999



of colleges and foundations in 1969 were anchored to the 1929 crash level even though the crash has little to do with future market levels. We argue that mean historical dividend yields and P/E ratios might serve as anchors for forecasts of future dividend yields and P/E ratios. Mean historical dividend yields and P/E ratios are surely more relevant to forecasts of returns than outcome of wheel of fortune spins to the percentage of African nations in the United Nations, but their relevance can be exaggerated.

Consider the changes in the spread between dividend yields and bond yields, as depicted in Exhibit 7. Dividend yields exceeded bond yields by a mean of 1.87% during the 1872–1958 period, and bond yields *never* exceeded dividend yields during that period. But dividend yields *trailed* bond yield by a mean of 3.64% during the 1959–1999 period, and *never* exceeded bond yields. Historical dividend yields and P/E ratios diverged from their mean by wide margins; future dividend yields and P/E ratios might well diverge substantially from their historical means.

HINDSIGHT

Norris [1999] relates that Andrew Carnegie in 1901 was convinced that the price of United States Steel shares was sure to fall. So he demanded that proceeds of the sale of his Carnegie Steel to United States Steel be invested in bonds rather than in stock. Carnegie's forecast turned out to be wrong; he would have remained wealthier than John D. Rockefeller had he taken the stock instead.

Today, with hindsight, we know that Carnegie's forecast was wrong. But could we have known it with

foresight? Hindsight bias leads people to exaggerate the quality of their foresight. Fischhoff [1975] describes an experiment in which he asked subjects to answer general knowledge questions from almanacs and encyclopedias. Next, he gave his subjects the correct answers and asked them to recall their original ones. Fischhoff found that, in general, people overestimate the quality of their initial knowledge and forget their initial errors.

Hindsight bias is a serious problem for all historians, including stock market historians. Once an event is part of history, there is a tendency to see the sequence that led to it as inevitable, as if uncertainty and chance were banished. As Posner [1999] notes, outcomes exert irresistible pressure on their interpretations. In hindsight, blunders with happy results are described as brilliant tactical moves, and sad results of choices that were well grounded in available information are described as avoidable blunders.

Accurate foresight about the fortunes of companies, the economy, or the stock market is rare. Will the technology investments of Microsoft and Cisco provide the high returns that are implicit in their late 1999 valuations? We know, with hindsight, that some past forecasts about technology and its economic impact were wildly optimistic. Cerf and Navasky quote Thomas Edison's 1910 forecast that "the nickel-iron battery will put gasoline buggies out of existence in no time" [1984, p. 229]. But other forecasts were equally wildly pessimistic. Cerf and Navasky quote the President of the Michigan Savings Bank's prediction in 1903 that "the horse is here to stay, but the automobile is only a novelty—a fad" [1984, p. 228].

Today's forecasts are also bound to be branded as wildly optimistic or pessimistic in the future. An OECD [1998] report on technology in the 21st century forecasts that nuclear power plants will be fail-safe, that earthquakes will be prevented, and that kitchens will be automated. It also forecasts that, by 2025, Huntington's chorea, cystic fibrosis, and certain types of Alzheimer's, arthritis, and cancer could be treatable and possibly reversible. Time will tell.

REMEDIES FOR COGNITIVE BIASES

Tactical asset allocation practitioners emphasize quantitative tools, while traditional market timing practitioners emphasize qualitative ones. Each forecasting method is subject to biases, and each calls for remedies.

The statistical tools of tactical asset allocation have built-in remedies against cognitive errors. For example,

regression analysis protects against overconfidence by providing the standard errors of regressions. It protects against the confirmation bias by including all data, confirming as well as disconfirming. Yet statistical tools have pitfalls of their own, pitfalls that require careful application and judicious interpretation.

Campbell and Shiller [1998] illustrate both the protection that statistical tools provide and their pitfalls. They find, in regression analysis, a negative and statistically significant relationship between P/E ratios and dividend yields and subsequent ten-year returns. But they caution against overconfidence for several reasons. First, they note that their current 1998 P/E and dividend ratios are so far from their historical averages that comparable historical data are lacking. Campbell and Shiller also note that while they use linear regressions in their analysis, the true relationship between valuation ratios and future returns might be non-linear. This, too, cautions against overconfidence. Last, Campbell and Shiller caution against hindsight. They note that it is possible to choose, with hindsight, valuation ratios that predict returns even if these valuation ratios were not recognized in the past.

Statistical tools are very useful; they allow us to extract systematic patterns from the past. But the world does not always regress to its historical mean, and future patterns might well break with the past. Moreover, statistical tools work best with data that can be quantified and traced over long periods of time. This requirement often causes us to exclude potentially relevant data such as changes in the political environment and the state of economic knowledge.

Consideration of qualitative data is by contrast a strength of traditional market timing, but the eclectic nature of such data, not to mention their interpretation, opens the door wide to cognitive biases. For example, in the absence of structures that force consideration of all data, the confirmation bias allows exclusion of data inconsistent with a favored hypothesis and interpretation of doubtful data as consistent with that favored hypothesis. Moreover, cognitive biases can be exacerbated by emotions, particularly regret.

Regret is the pain we feel when we find, too late, that other choices would have led to better outcomes. This is the pain of investors who bought stocks only to see prices plummet. Investors with paper losses often grow increasingly convinced that, in time, their stocks will roar back, and their choices will be vindicated. The same applies to forecasters who staked out strong bullish or bearish positions. The confirmation bias facilitates con-

EXHIBIT 8A
RELATIONSHIP BETWEEN ANNUALIZED
(OVERLAPPING) 10-YEAR REAL RETURNS
AND P/E RATIOS—1872–1999

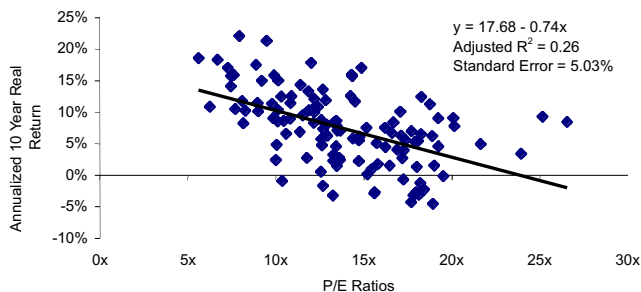


EXHIBIT 8B
RELATIONSHIP BETWEEN ANNUALIZED
(OVERLAPPING) 10-YEAR NOMINAL RETURNS
AND P/E RATIOS—1872–1999

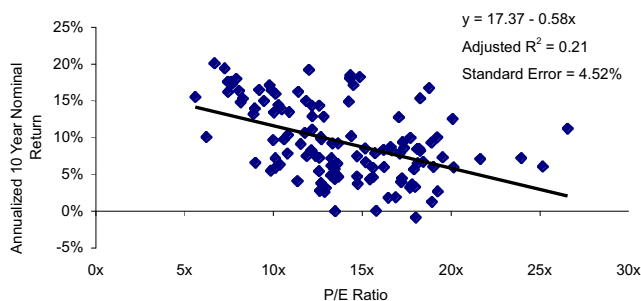


EXHIBIT 9A
RELATIONSHIP BETWEEN ANNUALIZED
(OVERLAPPING) 10-YEAR REAL RETURNS
AND DIVIDEND YIELDS—1872–1999

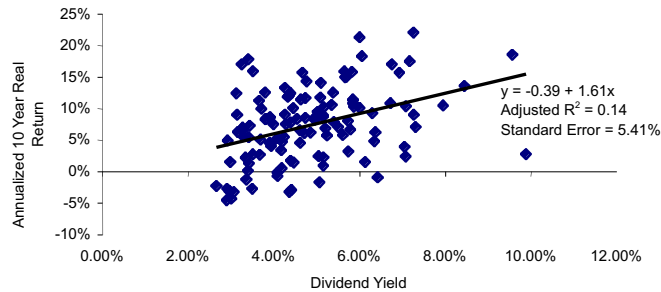
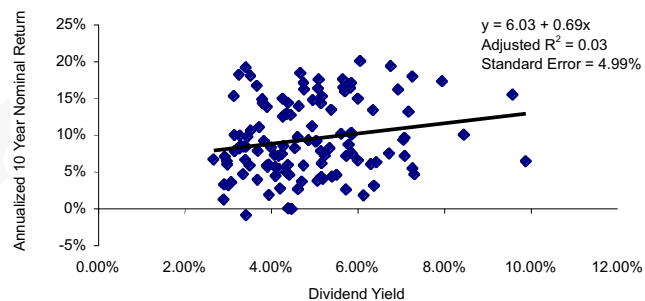


EXHIBIT 9B
RELATIONSHIP BETWEEN ANNUALIZED
(OVERLAPPING) 10-YEAR NOMINAL RETURNS
AND DIVIDEND YIELDS—1872–1999



viction by directing attention to information consistent with prior beliefs and away from information that contradicts such beliefs.

Organizational tools can supplement statistical tools in alleviating cognitive biases. For example, organizations can design structures for the elicitation of both confirming data and disconfirming data. This can be done, for example, when investment committees divide their discussions on hypotheses into two parts, one restricted to the elicitation of confirming data and one restricted to the elicitation of disconfirming data.

Consider, for example, Lipin's [2000] elicitation of opinions on the future of the U.S. markets and economy. He notes that financial historians point to many similarities between the U.S. markets in the 1990s and the 1960s. Both decades featured technology-driven IPO booms, concentration on a narrow number of high-flying growth stocks, a surge in takeovers, and an unshakable feeling that good times would go on forever. But

financial historians also point out differences:

Today, the economy is booming, inflation is low, regulatory restrictions on business have been eased and money flows into the stock market from a much larger segment of the population [2000, p. C1].

Will the good 1990s lead to the bad 2000s as the good 1960s led to the bad 1970s? It is wise to be humble when making forecasts.

FORECASTING TEN-YEAR RETURNS

As we note, Campbell and Shiller [1998] and Shiller [2000] find a negative relationship between P/E ratios and subsequent ten-year returns in a regression that features overlapping ten-year periods. Campbell and Shiller define earnings as real average earnings in the previous ten years and returns as real ten-year returns.

It turns out, as displayed in Exhibit 8A, that a regression of annualized 10-year real returns on “ordinary” P/E ratio (i.e., stock price divided by last 12-month earnings) yields a similar negative relationship, and, as displayed in Exhibit 8B, so does a regression of annualized 10-year nominal returns on ordinary P/E ratios. Note, however, that the relationship between 10-year returns and P/E ratios is far from perfect; the dots in the scatter diagram are quite scattered. Similar scatter is evident in a regression of annualized 10-year returns on dividend yield, as displayed in Exhibits 9A and 9B. P/E ratios and dividend yields might tell us something about the returns we might expect over the coming 10 years, but we should mind the traps of the illusion of validity.

CONCLUSION

The desire to banish investment uncertainty is strong, so strong that it blinds us to the tenuousness of investment forecasting. We find that P/E ratios and dividend yields provide little help in the task of forecasting short-horizon stock returns. There is no statistically significant relationship between dividend yields and P/E ratios and returns in the subsequent one or two years. The relationship between P/E ratios and dividend yields and stock returns over ten-year periods is much stronger, but it offers far less than perfect reliability. We trace the persistence of the belief that dividend yields and P/E ratios provide reliable forecasts of returns to cognitive errors that underlie the illusion of validity for which there are some statistical and organizational remedies.

We all want forecasting models with R^2 of 1.00, but actual R^2 are much closer to zero than to 1.00. As Bernstein [1999] notes, when R^2 is less than 1.00 we should consider not only the probabilities of being wrong, but the consequences as well. Investors who bet on margined stocks on the belief that the DJIA is sure to zoom to 36,000 are victims of the illusion of validity, and so are those who short stocks in the belief that the DJIA is sure to plummet to 3,600.

As Bernstein says, “now suppose that you are wrong, and the miracles are not forthcoming. Good-bye wealth!”

APPENDIX SOURCES OF DATA

RETURNS

Total returns for 1926-1999 are courtesy of Ibbotson Associates with dividends reinvested throughout each year. Total returns for 1871-1925 are derived from the Shiller website, with dividends not reinvested intrayear.

STOCK PRICES (SHILLER)

An annual series of values of the Standard & Poor Composite Stock Price Index starting in 1871 is taken from Standard & Poor’s Statistical Service Security Price Index Record, various issues, tables entitled Monthly Stock Price Indexes—Long Term (Shiller website).

BOND YIELDS

From 1872 through December 1877, the 6% U.S. government bonds of 1881 are used. From January 1878 through January 1895, the 4% U.S. government bonds of 1907 are used, and from February 1895 through December 1918, the 4% U.S. government bonds of 1925 are used. The source of these data is *The Financial Review*, William B. Dana Co. [1872-1921], which reprinted data published by *The Commercial and Financial Chronicle*.

Beginning in 1919, the Federal Reserve Board’s 10- to 15-year Treasury Bond Index is used. This is used through 1975. In 1976, the 20-year bond is used, and beginning on February 26, 1977, the 30-year bond is used. All courtesy of Globalfindata.com.

INFLATION DATA

Following Shiller website:

The annual average producer price index Series 7 is, for 1947 to the end of the sample, the annual average Producer Price Index all commodities 1967 = 100 from the Survey of Current Business. For 1924 to 1946 the series used is annual average WPI all commodities 1926 = 100 from the Federal Reserve Bulletin, divided by 1.9843. For 1914 to 1923 the series used is annual average WPI all commodities 1913 = 100 from the Federal Reserve Bulletin, divided by 3.038. For 1891 to 1913 the series used is annual average WPI all commodities 1913 = 100 from Wholesale Prices, BLS Bulletin #320, Government Printing Office, Washington, divided by 3.0395. For 1871 to 1890 the series used is annual average WPI 1890-99 = 100, from Appendix I of BLS Bulletin #114, divided by 4.1613.

EARNINGS AND DIVIDENDS

Again following Shiller website:

The dividend and earnings series that correspond to this stock price series are spliced together from two sources. Starting in 1926, the nominal dividend series are dividends per share, 12 months moving total adjusted to index for the last quarter of the year. Starting in 1926, the nominal earnings series are earnings per share, adjusted to index, four-quarter total, fourth quarter. These are from a table entitled “Earnings, Dividends and Price-Earnings Ratio—Quarterly” of Standard & Poor’s Statistical Service Security Price Index Record.

Standard & Poor’s does not publish dividend or earnings series before 1926, [but its] source for the Standard & Poor’s Index before 1926, a volume by Cowles [1939], gives a dividend series corresponding to the index, series Da-1, pp. 388-389, which I multiplied by the ratio of the series in 1926 to adjust for change in base year.

A problem Cowles faced was absence of earnings data for many of the stocks in the Standard & Poor’s Composite Index. He thus presented series PEA-1—“prices of stocks for which Earnings Data are available, all stocks,” a series of earnings E-1 on these stocks, and the ratio R-1 of these series, the “earnings-price ratio.” We computed the Standard & Poor’s Composite Earnings series for years before 1926 as series R-1 (Cowles [1939] pp. 404-405) times the annual average Standard & Poor’s Composite Index for the year. The spliced dividend and earnings series appear in Table 24.1 as series 2 and 3.

ENDNOTE

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