Factors

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Abstract and Keywords
Factors drive risk premiums. One set of factors describes fundamental, economy-wide variables like growth, inflation, volatility, productivity, and demographic risk. Another set consists of tradeable investment styles like the market portfolio, value-growth investing, and momentum investing. The economic theory behind factors can be either rational, where the factors have high returns over the long run to compensate for their low returns during bad times, or behavioral, where factor risk premiums result from the behavior of agents that is not arbitrated away.

Keywords: Risk premiums, real growth, inflation, volatility, productivity, political risk, demography, dynamic factors, alternative beta, size, value-growth, momentum

Chapter Summary
Factors drive risk premiums. One set of factors describes fundamental, economy-wide variables like growth, inflation, volatility, productivity, and demographic risk. Another set consists of tradeable investment styles like the market portfolio, value-growth investing, and momentum investing. The economic theory behind factors can be either rational,
where the factors have high returns over the long run to compensate for their low returns during bad times, or behavioral, where factor risk premiums result from the behavior of agents that is not arbitrated away.

1. Value Investing
Historically speaking, value stocks beat the pants off growth stocks. Value stocks have low prices in relation to their net worth, which can be measured by accounting book value. Growth stocks are relatively costly in comparison to book value. Figure 7.1 plots the returns of value stocks (stocks with high book-to-market ratios) versus growth stocks (stocks with low book-to-market ratios). I plot the returns to the value-growth strategy, which goes long value stocks and short growth stocks.\(^1\) Although value investing has on average done well, it sometimes loses money. For example, note the pronounced drawdown during the tech boom of the late 1990s. There was another drawdown during the financial crisis in 2008. Value stocks also did poorly in 2011.

Why does value investing work? Was the value strategy—the returns of value stocks in excess of growth stocks—a systematic factor? If so, what determined the value risk premium?

In the context of the previous chapter on factor theory, assets are buffeted by risk factors. The risk factors offer premiums to compensate investors for bearing (p.214) losses during bad times. I discuss the economic stories behind the factors from a rational and behavioral perspective and the implications of these stories for asset owners.\(^2\)
There are two types of factors. There are macro, fundamental-based factors, which include economic growth, inflation, volatility, productivity, and demographic risk. The second type is investment-style factors like the market factor of the capital asset pricing model (CAPM) and the value strategy of this motivating example. Investment factors include both static factors, like the market, which we simply go long to collect a risk premium, and dynamic factors, which can only be exploited through constantly trading different types of securities. (In chapters 17 and 18, I show that many hedge funds and private equity investments are essentially bundles of dynamic factors.) The two types of factors are linked, and macro factors are often embedded in the performance of investment factors. I turn to economy-wide macro factors first.

2. Macro Factors

It is intuitive that macro factors pervasively affect all investors and the prices of assets. When economic growth slows or inflation is high, all firms and investors in the economy are affected—it is just a question of degree. Most consumers dislike low growth and high inflation because it is more likely they will be laid off or they are less able to afford the same basket of goods and services in real terms. A few investors, such as debt collectors, benefit from slow growth, and a few other investors, including owners of oil wells, benefit from high inflation induced by surging commodity prices. In general, though, bad outcomes of macro factors define bad times for the average investor.

The level of the factor often does not matter as much as a shock to a factor. Many macro factors are persistent: when inflation is low today, we know that it will be very likely low next month. The fact that it is then low at the end of the month is no surprise. What is surprising are any movements in inflation not anticipated at the beginning of the period. Thus, we often need to look at unexpected changes to macro factors.

Asset prices respond to these factors contemporaneously. As inflation is increasing or unexpected adverse inflation shocks hit the economy, we enter a bad time and asset prices fall. The risk premium over the long run compensates investors for the losses endured when bad times of high inflation occur in the short run.
The three most important macro factors are growth, inflation, and volatility.

2.1. Economic Growth

Risky assets generally perform poorly and are much more volatile during periods of low economic growth. However, government bonds tend to do well during these times. If an investor is in a position to weather recessions relatively comfortably, then that person should tilt more heavily toward risky assets such as equities. In doing so she’ll enjoy higher returns, on average, and over the long run these will make up for losses during periods of low growth. If an investor cannot bear large losses during recessions, she should hold more bonds, especially government bonds. Her portfolio will likely perform much better during recessions but worse over the long run. This is the price the investor pays for low exposure to growth risk.

Table 7.2 reports means and volatilities of large stocks, small stocks, government bonds, and corporate bonds (investment grade and high yield) conditional on economic recessions and expansions defined by the National Bureau of Economic Research (NBER). I also report means and volatilities conditional on low and high real GDP growth and low and high consumption. These are computed simply by dividing the sample into two sets, above and below the median, respectively. Table 7.2 shows that, during recessions, stock returns fall: the mean return for large stocks is 5.6% during recessions and 12.4% during expansions. The difference in returns across recessions and expansions is more pronounced for the (p.216) (p.217) riskier small cap stocks at 7.8% and 16.8%, respectively. Government bonds act in the opposite way, generating higher returns at 12.3% during recessions compared to 5.9% during expansions. Investment-grade corporate bonds, which have relatively little credit risk, exhibit similar behavior. In contrast, high-yield bonds are much closer to equity, and their performance is between equity and government bonds; in fact, high-yield bonds do not have any discernable difference in mean returns over recessions and expansions.
### Table 7.2 Means and Volatilities Conditional on Factor Realizations

<table>
<thead>
<tr>
<th></th>
<th>Large Stocks</th>
<th>Small Stocks</th>
<th>Govt Bonds</th>
<th>Corporate Bonds</th>
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<tbody>
<tr>
<td><strong>Means</strong></td>
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<tr>
<td>Full Sample</td>
<td>11.3%</td>
<td>15.3%</td>
<td>7.0%</td>
<td>7.0%</td>
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<tr>
<td>Business Cycles (1)</td>
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<tr>
<td>Recessions</td>
<td>5.6%</td>
<td>7.8%</td>
<td>12.3%</td>
<td>12.6%</td>
</tr>
<tr>
<td>Expansions</td>
<td>12.4%</td>
<td>16.8%</td>
<td>5.9%</td>
<td>6.0%</td>
</tr>
<tr>
<td>Real GDP (2)</td>
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<td></td>
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<tr>
<td>Low</td>
<td>8.8%</td>
<td>12.2%</td>
<td>10.0%</td>
<td>9.7%</td>
</tr>
<tr>
<td>High</td>
<td>13.8%</td>
<td>18.4%</td>
<td>3.9%</td>
<td>4.4%</td>
</tr>
<tr>
<td>Consumption (3)</td>
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<td></td>
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<tr>
<td>Low</td>
<td>5.6%</td>
<td>5.6%</td>
<td>9.6%</td>
<td>9.1%</td>
</tr>
<tr>
<td>High</td>
<td>17.1%</td>
<td>25.0%</td>
<td>4.4%</td>
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<tr>
<td>Inflation (4)</td>
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<tr>
<td>Low</td>
<td>14.7%</td>
<td>17.6%</td>
<td>8.6%</td>
<td>8.8%</td>
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<tr>
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<tr>
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<td></td>
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<td></td>
<td>Investment Grade</td>
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<tr>
<td>Business Cycles</td>
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</tr>
<tr>
<td>Recessions</td>
<td>23.7%</td>
<td>33.8%</td>
<td>15.5%</td>
<td>16.6%</td>
</tr>
<tr>
<td>Expansions</td>
<td>14.0%</td>
<td>21.2%</td>
<td>9.3%</td>
<td>7.8%</td>
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<tr>
<td>Real GDP</td>
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<td>High</td>
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<td>8.9%</td>
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<td>8.2%</td>
</tr>
<tr>
<td>High</td>
<td>16.4%</td>
<td>25.4%</td>
<td>11.5%</td>
<td>11.1%</td>
</tr>
</tbody>
</table>

Returns are from Ibbotson Morningstar and are at the quarterly frequency.

The sample is 1952:Q1 to 2011:Q4.

(1) Business cycles are defined by NBER recession and expansion indicators.

(2) Real GDP is quarter-on-quarter.

(3) Consumption is quarter-on-quarter real personal consumption expenditures.
(4) Inflation is quarter-on-quarter CPI-All Items
We can see a similar pattern if we look at periods of low or high growth, as measured by real GDP or consumption growth. For example, large stocks return 8.8% during periods of low real GDP growth and 5.6% during periods of low consumption growth. During periods of high real GDP growth and high consumption growth, large stock returns average 13.8% and 17.1%, respectively. Consistent with the behavior across NBER recessions and expansions, government bonds tend to do relatively well during periods of low growth, averaging 10.0% during periods of low real GDP growth compared to 3.9% during periods of high real GDP growth.

All asset returns are much more volatile during recessions or periods of low growth. For example, large stock return volatility is 23.7% during recessions compared to 14.0% during expansions. While government bonds have higher returns during recessions, their returns are also more volatile then, with a volatility of 15.5% during recessions compared to 9.3% during expansions. It is interesting to compare the volatilities of assets over the full sample to the volatilities conditional on recessions and expansions: volatility tends to be very high during bad times.

2.2. Inflation

High inflation tends to be bad for both stocks and bonds, as Table 7.2 shows. During periods of high inflation, all assets tend to do poorly. Large stocks average 14.7% during low inflation periods and only 8.0% during periods of high inflation. The numbers for government bonds, investment grade bonds, and high yield bonds are 8.6%, 8.8%, and 9.2%, respectively, during low inflation periods and 5.4%, 5.3%, and 6.0%, respectively, during high inflation periods. It is no surprise that high inflation hurts the value of bonds: these are instruments with fixed payments, and high inflation lowers their value in real terms. It is more surprising that stocks—which are real in the sense that they represent ownership of real, productive firms—do poorly when inflation is high. We’ll take a closer look at the inflation-hedging properties of equities in chapter 8, but for now, suffice to say that high inflation is bad for both equities and bonds. Part of the long-run risk premiums for both equities and bonds represents compensation for doing badly when inflation is high. (In
chapter 11, we’ll further explore the inflation hedging properties of different asset classes.)

2.3. Volatility

Volatility is an extremely important risk factor. I measure volatility risk using the VIX index, which represents equity market volatility. Here’s a table correlating changes in VIX with stock and bonds returns on a monthly frequency basis from March 1986 to December 2011:

<table>
<thead>
<tr>
<th>VIX Changes</th>
<th>Stock Returns</th>
<th>Bond Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX Changes</td>
<td>1.00</td>
<td>−0.39</td>
</tr>
<tr>
<td>Stock Returns</td>
<td>−0.39</td>
<td>1.00</td>
</tr>
<tr>
<td>Bond Returns</td>
<td>0.12</td>
<td>−0.01</td>
</tr>
</tbody>
</table>

The correlation between VIX changes and stock returns is −39%, so stocks do badly when volatility is rising. The negative relation between volatility and returns is called the leverage effect. When stock returns drop, the financial leverage of firms increases since debt is approximately constant while the market value of equity has fallen. This makes equities riskier and increases their volatilities. There is another channel where high volatilities lead to low stock returns: an increase in volatility raises the required return on equity demanded by investors, also leading to a decline in stock prices. This second channel is a time-varying risk premium story and is the one that the basic CAPM advocates: as market volatility increases, discount rates increase and stock prices must decline today so that future stock returns can be high.

Bonds offer some but not much respite during periods of high volatility, as the correlation between bond returns and VIX changes is only 0.12. Thus, bonds are not always a safe haven when volatility shocks hit. In 2008 and 2009, volatility was one of the main factors causing many risky assets to fall simultaneously. During this period, risk-free bonds did very well. But during the economic turbulence of the late 1970s and early 1980s, bonds did terribly, as did equities (see chapter 9). Volatility as measured by VIX can also capture uncertainty—in the sense that investors did not know the policy responses that government would take during the financial crisis, whether markets would continue functioning, or whether their own models were the correct ones. Recent
research posits uncertainty risk itself as a separate factor from volatility risk, but uncertainty risk and volatility risk are highly correlated.9

**Figure 7.3** plots the VIX index (left-hand side axis) in the dashed line and a one-year moving average of stock returns (on the right-hand side axis) in the solid line. Volatility tends to exhibit periods of calm, punctuated by periods of turbulence. Figure 7.3 shows spikes in volatility corresponding to the 1987 stock market crash, the early 1990s recession, the Russian default crisis in 1998, the terrorist attacks and ensuing recession in 2001, and a large spike in 2008 corresponding to the failure of Lehman Brothers. In all of these episodes, stock returns move in the opposite direction from volatility, as shown during the financial crisis.

The losses when volatility spikes to high levels can be quite severe. Partitioning the sample into high and low periods of volatility changes gives us an average return for large stocks of –4.6% during volatile times and 24.9% during stable times. This compares to an overall mean of 11.3% (see Table 7.2). Investors allergic to volatility could increase their holdings of bonds, but bonds do not always pay off during highly volatile periods—as the low correlation of 0.12 between VIX changes and bond returns in the table above shows.

Stocks are not the only assets to do badly when volatility increases. Volatility is negatively linked to the returns of many assets and strategies. Currency strategies fare especially poorly in times of high volatility.10 We shall see later that many assets or strategies implicitly have large exposure to volatility.
risk. In particular, hedge funds, in aggregate, sell volatility (see chapter 17).

Investors who dislike volatility risk can buy volatility protection (e.g., by buying put options). However, some investors can afford to take on volatility risk by selling volatility protection (again, e.g., in the form of selling put options). Buying or selling volatility protection can be done in option markets, but traders can also use other derivatives contracts, such as volatility swaps. Investors are so concerned about volatility, on average, that they are willing to pay to avoid volatility risk, rather than be paid to take it on. Periods of high volatility coincide with large downward movements (see Figure 7.3) and assets that pay off during high volatility periods, like out-of-the-money puts, provide hedges against volatility risk.

We often think about assets having positive premiums—we buy, or go long, equities, and the long position produces a positive expected return over time. Volatility is a factor with a negative price of risk. To collect a volatility premium requires selling volatility protection, especially selling out-of-the-money put options. The VIX index trades, on average, above volatilities observed in actual stocks: VIX implied volatilities are approximately 2% to 3%, on average, higher than realized volatilities. Options are thus expensive, on average, and investors can collect the volatility premium by short volatility strategies. Fixed income, currency, and commodity markets, like the aggregate equity market, have a negative price of volatility risk.\(^{11}\)

Selling volatility is not a free lunch, however. It produces high and steady payoffs during stable times. Then, once every decade or so, there is a huge crash where sellers of volatility experience large, negative payoffs. Figure 7.4 plots the cumulated returns of a volatility premium (swap) index constructed by Merrill Lynch. There are steady returns until 2007, with the few blips corresponding to some small losses during 1998 (Russian default crisis) and 2001 and 2002 (9/11 tragedy and economic recession, respectively), and also during the summer of 2007 (subprime mortgage-backed losses just prior to the financial crisis). But between September and November 2008 there are massive losses close to 70%. These were the darkest months in the financial crisis, and most of the losses across all types of risky assets during 2008 were
concentrated during these months (see Table 6.1). The huge crash causes volatility selling to have a large negative skewness of -8.26 over the whole sample. Taking data prior to the financial crisis ending December 2007, the skewness is only -0.37, so prior to 2007 selling volatility looked like easy money.

Unfortunately, some investors who sold volatility prior to the financial crisis failed to anticipate that a crash like the one of 2008 would materialize. But it did, and the abysmal returns of many assets resulted to a great extent from them being exposed to volatility risk. While forecasting when a crash will take place is always hard, if not impossible, investors might have known from past data that a crash of this type will happen from time to time. For example, volatility had spiked to these levels during the Great Depression. In fact, during the 1930s, volatility was not only extremely high, but it remained high for a much longer period than the 2008–2009 experience.

Only investors who can tolerate periods of very high volatility—which tend to coincide with negative returns on most risky assets—should be selling volatility protection through derivatives markets. Selling volatility is like selling insurance. During normal times, you collect a premium for withstanding the inevitable large losses that occur every decade or so. The losses endured when volatility spikes represent insurance payouts to investors who purchased volatility protection.

In chapter 4, I showed that rebalancing as a portfolio strategy is actually a short volatility strategy. Thus, the simple act of rebalancing will reap a long-run volatility risk premium, and the person who does not rebalance—the average investor who owns 100% of the market—is long volatility risk and loses the long-run volatility risk premium. A long-run, rebalancing
investor is exposed to the possibilities of fat, left-hand tail losses like those in Figure 7.4. There are two differences, however. Rebalancing over assets (or strategies or factors as in chapter 14) does not directly trade volatility risk. That is, rebalancing over stocks (p.222) trades physical stocks, but Figure 7.4 involves trading risk-neutral, or option, volatility. Trading volatility in derivatives markets brings an additional volatility risk premium that rebalancing does not. Thus, losses in trading volatility in derivative markets are potentially much steeper than simple rebalancing strategies. Second, pure volatility trading in derivatives can be done without taking any stances on expected returns through delta-hedging.

Rebalancing over fundamental asset or strategy positions is done to earn underlying factor risk premiums. While there is only weak predictability of returns, the investor practicing rebalancing gets a further boost from mean reversion as she buys assets with low prices that have high expected returns. Chapters 4 and 14 cover this in more detail.

Constructing valuation models with volatility risk can be tricky because the relation between volatility and expected returns is time varying and switches signs and is thus very hard to pin down. A large literature has tried to estimate the return–volatility trade-off as represented in equation (6.1) repeated here:

\[
(7.1) \quad E(r_m) - r_f = \gamma \sigma_m^2
\]

where \(E(r_m) - r_f\) is the market risk premium and \(\sigma_m^2\) is the variance of the market return. According to CAPM theory, \(\gamma\) represents the risk aversion of the average investor.

Is the coefficient, \(\gamma\), relating the market volatility or variance to expected returns, which is supposedly positive in theory, actually positive in data? In the literature, there are estimates that are positive, negative, or zero. In fact, one of the seminal studies, Glosten, Jagannathan, and Runkle (1993), contains all three estimates in the same paper! Theoretical work shows that the risk–return relation can indeed be negative and change over time.\textsuperscript{13} What is undisputed, though, is that when volatility increases dramatically, assets tend to produce losses. Only an investor who can tolerate large losses during high-volatility periods should consider selling volatility protection.

2.4. Other Macro Factors
Several other macro factors have been investigated extensively in the literature and deserve attention from asset owners.
Productivity Risk

A class of real business cycle models developed in macroeconomics seeks to explain the movements of macro variables (like growth, investment, and savings) and asset prices across the business cycle. In these models, macro variables and asset prices vary across the business cycle as a rational response of firms and agents adjusting to real shocks. The label “real” in “real business cycle” emphasizes (p.223) that the business cycle is caused by real shocks and is not due to market failures or insufficient demand as in the models of John Maynard Keynes (1936). Real business cycle models have inflation, but inflation is neutral or has no real effects. These models are production economies because they involve optimizing firms producing physical goods, in addition to agents optimizing consumption and savings decisions, but the firms are subject to shocks that affect their output. One particularly important shock that affects firm output is a productivity shock. The early literature, like Kydland and Prescott (1982), did not have asset prices. (Kydland and Prescott won the Nobel Prize in 2004.) The next generation of models, like Jermann (1988), put them in. The newest papers, like Kaltenbrunner and Lochstoer (2010), capture realistic, and complicated, dynamics of shocks and agents’ behavior.

Because these models are designed to work at business cycle frequencies, they are less relevant for investors who have short horizons. But for long-horizon investors—like certain pension funds, sovereign wealth funds, and family offices—the productivity factor should be considered. Asset returns reflect long-run productivity risk. At the time of writing, Europe is still in the throes of its sovereign debt convulsions, and an important issue is the future productive capacity of European economies. In Figure 7.5, I plot a five-year average of productivity shocks and stock returns. I use a five-year average because the productivity variable is used in economic models that are designed to explain business cycle variation, which has a frequency of three to six years. The productivity shocks are alternatively called Solow residuals after Robert Solow (1957) or total factor productivity (TFP) shocks. I take the TFP shocks constructed by Fernald (2009), (p.224) who follows the method of Basu, Fernald, and Kimball (2006). Figure 7.5 shows that when there are periods of falling productivity, like the 1960s and 1970s, stock prices tend to fall. In the 1980s and 1990s (the computer revolution),
productivity shocks are positive and stocks tend to appreciate. The correlation of the five-year moving averages of TFP shocks and stock returns is high, at 48%. So stocks are exposed to productivity risk; when productivity slows down, stock returns tend to be low.

Productivity risk is just one source of shocks that enter the new generation of dynamic stochastic general equilibrium (DSGE) macro models. This mouthful conveys the complexity of this class of models. In DSGE models, the economy is dynamic (as the name indicates) and the actions of agents (consumers, firms, central banks, and governments), technologies (how firms produce), and institutions or markets (the way that agents interact) cause economic variables to change. Asset prices are set from the complex interaction of all of these players and technologies. The DSGE models allow us to think about how shocks from these factor risks are transmitted across the economy. An important part of DSGE models are the actions of policy makers—government policy matters, as the financial crisis showed. Monetary policy and government shocks are important factors that influence asset prices and constitute their own sources of risk. We come back to some of these factors in the next few chapters. Current DSGE models nest both the real business cycle models pioneered by Kydland and Prescott, and they also include new-Keynesian models, where prices do not immediately adjust and inflation is non-neutral.

DSGE models describe business cycle fluctuations well, and we know asset returns vary over the business cycle. A benchmark model today is Smets and Wouters (2007), who specify seven shocks: productivity (as we have just discussed),
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investment, preferences, labor supply, inflation, government spending, and monetary policy. In chapters 8 and 9 covering equities and fixed income, respectively, we delve further into how some of these risks are priced.\(^{15}\)

**Demographic Risk**

Another important risk for a very long-term investor is *demographic risk*. This can be interpreted as a shock to labor output, just as a productivity shock is a shock to firm production. A slow-moving variable, demography is a factor in economic *overlapping generations* (OLG) models. A given individual follows a life-cycle model, like the kind examined in chapter 5. Take, for example, an individual who progresses through youth, middle-age, and retirement. Labor income is earned and saved only during the young and middle-aged periods, and dis-saving occurs when retired. As any given age cohort progresses through the three stages, they join two other cohorts already alive who were born in previous generations. Thus, several (p.225) generations overlap at any given time. A demographic shock changes the composition of a given cohort relative to other cohorts through such events as war (like World Wars I and II), a baby boom (like the generation born in the two decades following World War II), or infectious disease (Spanish Flu in 1918).

Several OLG models predict that demographic composition affects expected returns. Theory suggests two main avenues for this to occur. First, the life-cycle smoothing in the OLG framework requires that when the middle-aged to young population is small, there is excess demand for consumption by a relatively large cohort of retirees. Retirees do not want to hold financial assets: in fact, they are selling them to fund their consumption. For markets to clear, asset prices have to fall.\(^{16}\) Abel (2001) uses this intuition to predict that as baby boomers retire, stock prices will decline. The predictions are not, however, clear cut: Brooks (2002), for example, argues that the baby boom effect on asset prices is weak. The second mechanism where demography can predict stock returns is that, since different cohorts have different risk characteristics, asset prices change as the aggregate risk characteristics of the economy change. In an influential study, Bakshi and Chen (1994) show that risk aversion increases as people age and, as
the average age rises in the population, the equity premium should increase.

In testing a link between demographic risk and asset returns, it is important to use international data; using only one country’s demographic experience is highly suspect because demographic changes are so gradual. The literature employing cross-country analysis includes Erb, Harvey, and Viskanta (1997), Ang and Maddaloni (2005), and Arnott and Chaves (2011). There is compelling international empirical evidence that demography does affect risk premiums.

**Political Risk**

The last macro risk that an asset owner should consider is political or sovereign risk. Political risk has been always important in emerging markets: the greater the political risk, the higher the risk premiums required to compensate investors for bearing it. Political risk was thought to be of concern only in emerging markets. The financial crisis changed this, and going forward political risk will also be important in developed countries.

3. Dynamic Factors

The CAPM factor is the market portfolio, and, with low-cost index funds, exchange-traded funds, and stock futures, the market factor is tradeable. Other (p.226) factors are tradeable too. These factors reflect macro risk and at some level should reflect the underlying fundamental risks of the economy. Macro factors like inflation and economic growth, however, are not usually directly traded (at least not in scale, with the exception of volatility), and so dynamic factors have a big advantage that they can be easily implemented in investors’ portfolios.

I present examples of dynamic factors using the best-known example of a tradeable multifactor model introduced by Fama and French (1993). I interchangeably use the words “style factors,” “investment factors,” and “dynamic factors.” Sometimes these are also called “smart beta” or “alternative beta,” mostly by practitioners.

3.1. Fama and French (1993) Model

The Fama–French (1993) model explains asset returns with three factors. There is the traditional CAPM market factor and
there are two additional factors to capture a size effect and a value/growth effect:

\[ E(r_i) = r_f + \beta_{i, \text{MKT}} (E(r_m - r_f)) + \beta_{i, \text{SMB}} E(\text{SMB}) + \beta_{i, \text{HML}} E(\text{HML}), \]

where two new factors, SMB and HML, appear alongside the regular CAPM market factor.

Let us briefly recap the effect of the CAPM market factor (see chapter 6). When the market does poorly, stocks that have high exposures to the market factor (stocks with high betas, \( \beta_{i, \text{MKT}} \)) also tend to do badly. That is, high beta stocks tend to tank in parallel when the market tanks. But over the long run, the CAPM predicts that stocks with high betas will have higher average returns than the market portfolio to compensate investors for losses when bad times hit—defined by the CAPM theory as low returns of the market.

Robert Merton (1973), Stephen Ross (1976), and others developed the theoretical multifactor model framework in the 1970s, but it took another two decades for an explosion of studies to demonstrate that factors other than the market mattered empirically. Two of these effects—size and value—are in the Fama–French model. Fama and French did not discover these effects; they just provided a parsimonious model to capture their effects. Unfortunately for the original authors, most of the credit for these risk factors now gets assigned to Fama and French.

In equation (7.2), the first factor in addition to the market factor in the Fama–French model is SMB, which refers to the differential returns of small stocks minus big stocks (hence SMB), where small and big refer simply to the market capitalization of the stocks. (Fama and French were clearly not marketers, so the labels on the factors are a tad banal.) The SMB factor was designed to capture the outperformance of small firms relative to large firms.

The other factor in the Fama–French model is the HML factor, which stands for the returns of a portfolio of high book-to-market stocks minus a portfolio of low book to market stocks. The book-to-market ratio is book value divided by market capitalization, or the inverse of equity value normalized by book value. (p.227) In essence, a value strategy consists of buying stocks that have low prices (normalized by book value,
sales, earnings, or dividends, etc.) and selling stocks that have high prices (again appropriately normalized). Academics often normalize by book value. Thus, value stocks are stocks with low prices relative to book value. Growth stocks have high prices relative to book value. The value effect refers to the phenomenon that value stocks outperform growth stocks, on average. One can normalize prices by measures other than book value—which practitioners do when they build their (often proprietary) value factors.

Fama and French’s SMB and HML factors are constructed to be factor mimicking portfolios. They are constructed to capture size and value premiums, respectively and use the (CAPM and multifactor) concept of diversification to ensure that the factors capture size and value effects by averaging across many stocks. These factors are long–short portfolios and take positions away from the market portfolio. The average stock, however, only has market exposure since every stock can’t be small and every stock can’t be large. Let’s examine this point more closely because it is intimately related with the profound CAPM insight that the average investor holds the market.

Suppose Buffet, I mean Huffet, is a value stock, headed by a manager who likes to buy companies trading for less than their fundamental value, measured, say, by book value. In the Fama–French model in equation (7.2), Huffet has a positive HML beta, $\beta_{HML}$. Value stocks, on average, do better than growth stocks. Relative to the CAPM, the expected return on Huffet is adjusted upward by $\beta_{HML} \times E(HML)$. Since HML is constructed to have a positive risk premium (remember, it goes long high book-to-market stocks, which are value stocks with high returns, and goes short low book-to-market stocks, which are growth stocks with low returns), the Fama–French nudges Huffet’s risk premium upward to account for its “valueness.”

Now consider a growth firm, Enron, sorry Inron, which has grown rapidly through a series of acquisitions. Inron has a negative HML beta. Relative to the CAPM, the expected return on Inron is adjusted downward, since now $\beta_{HML} \times E(HML)$ is negative; because Inron is anti-value, or a growth stock, it carries a lower return.
In the Fama–French model, the SML and HML betas are centered around zero. The market is actually size neutral and value neutral. Just as the average investor holds the market, the average stock does not have any size or value tilt. It just has market exposure. Furthermore, in the CAPM, the average beta of a stock is one, which is also the beta of the market. The market itself could be affected by macro factors, like GDP growth, inflation, and the factors discussed in the previous sections. The Fama–French model (7.2) prices value stocks like Huffet and growth stocks like Inron relative to the market.

One important assumption in the CAPM and Fama–French models is that the betas are constant. Empirical evidence shows that exposures of some assets to systematic factors vary over time and, in particular, increase during bad times. The variation of betas themselves can be a source of risk. That betas tend to increase during bad times undoubtedly caused the negative returns of risky assets to be larger during the financial crisis than they otherwise would have been had their betas remained constant.

3.2. Size Factor

The size effect was discovered by Banz (1981), with similar results in Reinganum (1981), and refers to the fact that small stocks tended to do better than large stocks, after adjusting for their betas. The past tense is appropriate here, because since the mid-1980s there has not been any significant size effect.

Figure 7.6 plots the value of $1 invested in the SMB strategy after taking out the market effect beginning in January 1965 to December 2011 in the solid line. The compound returns of SMB reach a maximum right around the early 1980s —just after the early Banz and Reinganum studies were published. Since the mid-1980s there has been no premium for small stocks, adjusted for market exposure. International evidence since the mid-1980s has also been fairly weak. Examining international data, Dimson, Marsh, and Staunton (2011) state that if researchers today were uncovering the size effect, “the magnitude of the premium would not command particular attention, and would certainly not suggest there was a major ‘free lunch’ from investing in small caps.” Fama
and French (2012) also find no size premiums in a comprehensive international data set over recent periods.

There are two responses to the disappearance of the size effect. First, the original discovery of the size premium could have just been data mining. Fischer Black (1993) made this comment immediately after Fama and French’s paper was released. The “discovery” of the size effect was then an example of Rosenthal’s (1979) “file drawer problem,” which is now a “hard drive problem” (and turning into a “cloud problem”). Researchers store on their hard drives 95% of the results that are statistically insignificant (using a standard p-value of 0.05 to judge significance) and only publish the 5% that are statistically significant. The discoverers of the size premium accidentally fell into the 5% category and were just lucky. One telling outcome of data mining is that an effect appears significant in sample, where the models are originally estimated, but it fails out of sample, where the models are tested after their discovery. Banz’s size effect, therefore, might never have truly existed in the first place, and its finding by Banz and Reinganum was pure luck.  

The second response is that actually the size effect was there and actions of rational, active investors, acting on news of the finding, bid up the price of small cap stocks until the effect was removed. In this context, the disappearance of the size effect represents the best of the Grossman–Stiglitz (1980) near-efficient market in which practitioners quickly exploit any anomaly. Viewed this way, size does not deserve to be a
systematic factor and should be removed from the Fama-French model.

It should be noted that small stocks do have higher returns, on average, than large stocks. The effects of other factors, like value and momentum, which we discuss below, are also stronger in small stocks. Small stocks also tend to be more illiquid than large stocks. The pure size effect refers to the possible excess returns of small stocks after adjusting for CAPM betas. The weak size effect today means that an asset owner should not tilt toward small stocks solely for higher risk-adjusted returns. There may only be a case for preferring small caps based on (p.230) wanting to pursue higher returns without being able to short the market (to remove small caps’ market exposures) or an investor could tilt to small caps because she wishes high returns but cannot lever. The unconstrained, investment-only reason for small caps, however, is not compelling.

3.3. Value Factor
Unlike size, the value premium is robust. Figure 7.6 graphs cumulated returns on the value strategy, HML. Value has produced gains for the last fifty years. There are several notable periods where value has lost money in Figure 7.6, some extending over several years: the recession during the early 1990s, the roaring Internet bull market of the late 1990s, and there were large losses from value strategies in the financial crisis over 2007–2008. The risk of the value strategy is that although value outperforms over the long run, value stocks can underperform growth stocks during certain periods. It is in this sense that value is risky.

The benefits of value have been known since the 1930s. Graham and Dodd published a famous book, Security Analysis, in 1934, that serves as a guide to identifying firms with low prices relative to their fundamental value. Academics and practitioners proxy fundamental value today by various balance sheet variables or transformations thereof. Graham and Dodd were at Columbia Business School, where I teach, and a strong value-investing tradition continues at my institution today with the Heillbrunn Center for Graham & Dodd Investing. Modern academic research into the value effect began with Basu (1977), and the last few decades have seen an explosion of papers offering various explanations for
the value premium. These explanations, like most of the
finance literature, fall largely into two camps: the rational and
the behavioral.

3.4. Rational Theories of the Value Premium
In the rational story of value, value stocks move together with
other value stocks after controlling for market exposure (and
in fact covary negatively with growth stocks). All value stocks,
therefore, tend to do well together or they do badly together.
Finding a value stock that doesn’t move together with the pack
is like finding the sourpuss not thrashing at a heavy metal
concert. Just as the euphoria can’t last, and some fans
experience throbbing migraines the next day, value doesn’t
always earn high returns. Value is risky, and the riskiness is
shared to a greater or lesser degree by all value stocks. Some
value risk can be diversified by creating portfolios of stocks,
but a large amount of value movements cannot be diversified
away. (In fact, Fama and French exploit this common
covariation in constructing the HML factor.) In the context of
the APT, since not all risk can be (p.231) diversified away, the
remaining risk must be priced in equilibrium, leading to a
value premium.

The Fama–French model itself is silent on why value carries a
premium. In contrast, the CAPM provides a theory of how the
market factor is priced and even determines the risk premium
of the market (see equation (7.1) and also chapter 7). To go
further, we need to delve into an economic reason for why the
value premium exists.

In the pricing kernel formulation, any risk premium exists
because it is compensation for losing money during bad times.
The key is defining what those bad times are. Let’s look at
Figure 7.6 again. The bad times for value do not always line up
with bad times for the economy. Certainly value did badly
during the late 1970s and early 1980s when the economy was
in and out of recession. We had a recession in the early 1990s
when value also did badly, and the financial crisis in 2008 was
unambiguously a bad time when value strategies posted
losses. But the bull market of the late 1990s? The economy
was booming, yet value stocks got killed. Rational stories of
value have to specify their own definitions of bad times when
value underperforms, so that value earns a premium on
average.
Some factors to explain the value premium include investment growth, labor income risk, nondurable or “luxury” consumption, and housing risk. A special type of “long-run” consumption risk also has had some success in explaining the value premium. During some of the bad times defined by these factors, the betas of value stocks increase. This causes value firms to be particularly risky.
Firm Investment Risk

A key insight into the behavior of value and growth firms was made by Berk, Green, and Naik (1999). They build on a real option literature where a manager’s role is to optimally exercise real investment options to increase firm value.28 A firm in this context consists of assets in place plus a set of investment options that managers can choose (or not) to exercise. The CAPM is a linear model, and it turns out that CAPM does not fully work when there are option features (see also chapter 10). Berk, Green, and Naik show that managers optimally exercise investment options when market returns are low. These investment options are dynamically linked to book-to-market (and size) characteristics, giving rise to a value premium. Value firms are risky; their risk turns out to be the same conventional bad times risk as the CAPM or other macro-based factors. Be a value investor only if you can stomach losses on these firms during these bad times.

(p.232) Lu Zhang has written a series of papers explaining the value premium in terms of how value firms are risky as a result of their underlying production technologies. An important paper is Zhang (2005), which builds on the production-based asset pricing framework introduced by Cochrane (1991, 1996). Cochrane teaches us to look at firm investment to study firm returns. The gist of the Cochrane–Zhang story is as follows. Value firms and growth firms differ in how flexible they are and how quickly they can respond to shocks. During bad times, value firms are risky because they are burdened with more unproductive capital. Think of value firms as making stodgy widgets, and when a bad time comes, they cannot shift their firm activities to more profitable activities—they are stuck making widgets. They wish to cut back on capital, but they cannot sell their specialized widget-manufacturing equipment. In economists’ jargon, they have high and asymmetric adjustment costs. Growth firms, however, can easily divest because they employ hotshot young employees and the great bulk of their capital is human capital, not stodgy widget-making factories. Thus, value firms are fundamentally riskier than growth firms and command a long-run premium.

Rational Implications for Asset Owners
The literature is still debating whether the bad times defined by these theories are truly bad times. But this academic debate is not that relevant to an asset owner; bickering over a Cochrane–Zhang story versus a story about another risk factor is not what the asset owner contemplating a value tilt should be doing.

Remember that the average investor holds the market portfolio. The asset owner should take these rational theories and ask, given that each factor defines a different set of bad times, are these actually bad times for me? If I do not need to eat less during periods when investment growth is low, then this is not as bad a time for me as it is for the average investor. Thus, I have a comparative advantage in holding value stocks and can harvest the value premium. Other investors are not comfortable holding value stocks (and should hold growth stocks instead) because they cannot afford to shoulder the losses generated by value stocks during bad times. Overall, the average investor holds the market even though some investors prefer value stocks and some investors prefer growth stocks. Which type you are—value or growth—depends on your own behavior during each of these bad times.

3.5. Behavioral Theories of the Value Premium

Most behavioral theories of the value premium center around investor overreaction or overextrapolation of recent news. The standard story was first developed by Lakonishok, Shleifer, and Vishny (1994). Investors tend to overextrapolate past growth rates into the future. The posterchild growth stock example at the time of writing is Apple Inc. (AAPL), which has achieved tremendous growth over the last few years by introducing a series of must-have products. Investors mistake Apple’s past high growth for future high growth. Growth firms, in general, have (p.233) had high growth rates. The prices of these firms are bid up too high, reflecting excessive optimism. When this growth does not materialize, prices fall, leading to returns on growth stocks being low relative to value firms. The story here is that value stocks are not fundamentally riskier than growth firms, as in the rational stories. Value stocks are cheap because investors underestimate their growth prospects. Conversely growth firms are expensive because investors overestimate their growth prospects.
The value effect can also be produced by investors with other psychological biases. Barberis and Huang (2001) generate a value effect by employing two psychological biases: loss aversion and mental accounting. Loss aversion we have seen before, in chapter 2. Since investors suffer from losses more than they rejoice from equivalent gains, a loss following a loss is more painful than just a single loss. As for mental accounting, here agents look at each stock individually rather than considering overall gains and losses on their portfolios. The Barberis–Huang story of value is that a high book-to-market ratio stock is one that has achieved its relatively low price as the result of some dismal prior performance. This burned the investor who now views it as riskier and thus requires higher average returns to hold the stock.

The crucial question that behavioral models raise is: why don’t more investors buy value stocks and, in doing so, push up their prices and remove the value premium, just as investors appear to have done with the size premium (at least according to the Grossman–Stiglitz interpretation)? Put another way, why aren’t there more value investors? It can’t be ignorance; the message of Graham and Dodd has spread far and wide since the 1930s, as demonstrated by the cult-like fervor of Berkshire Hathaway annual meetings, where value guru Warren Buffet holds court, or at the Graham & Dodd Breakfast conferences at Columbia Business School.

Perhaps investors think value investing is too difficult. Yet simple strategies of academics sorting stocks on a book-to-market basis are available even to the smallest retail investor using stock screens freely available on the Internet. Perhaps it is the legacy of the efficient market theory developed in the 1970s (see chapter 6)—but active managers have never believed in truly efficient markets, and now academics no longer believe in them either.

Maybe not enough institutions have sufficiently long horizons to effectively practice value investing. The value effect documented here, though, is different from the “deep value” practiced by some investors, including Buffet. That requires five- to ten-year horizons. The book-to-market value effect described here is a three- to six-month effect. But perhaps even this horizon is too long for most “long-horizon” investors.

Behavioral Implications for Asset Owners
The relevant question that an asset owner should ask from a behavioral standpoint is simple: do you act like the market, or do you have the ability not to overextrapolate or overreact? If you know you overextrapolate, do you overextrapolate less than the average investor? If you act like everyone else, then simply hold the market portfolio. If you overreact more, perhaps unconsciously, then you tilt toward growth stocks. If you can go against the crowd, then value investing is for you.

3.6. Value in Other Asset Classes

Value in essence buys assets with high yields (or low prices) and sells assets with low yields (or high prices). While in equities the strategy is called value-growth investing, the same strategy of buying high-yielding assets and selling low-yielding assets works in all asset classes but goes by different names. Many commentators view these different asset-class strategies as distinct, but they share many features. In fixed income, the value strategy is called *riding the yield curve* and is a form of the duration premium (see chapter 9). In commodities it is called the *roll return*, and the sign of the return is related to whether the futures curve is upward- or downward-sloping (see chapter 11).

In foreign exchange, the value strategy is called *carry*. This is a popular strategy that goes long currencies with high interest rates and shorts currencies with low interest rates. Traditionally, the former have been countries like Australia and New Zealand, and the latter have been countries like Japan and more recently the United States. In these cases, we can use versions of equation (7.2) within each asset class. For example, adapting Lustig, Roussanov, and Verdelhan (2011), we could capture the carry (or “value”) returns of a foreign currency by using

\[(7.3)\]

\[E(FX) = \beta_{iFX}E(HML_{FX}),\]

where \(FX\) is the foreign carry return of country \(i\), \(\beta_{iFX}\) is the loading of currency \(i\) on the carry factor \(HML_{FX}\), which is formed by going long currencies with high interest rates minus currencies with low interest rates. There is no conceptual difference between the value strategy in currencies in equation (7.3) and the value strategy in equities in equation
(7.2) in terms of viewing low prices as equivalent to high yields.

Value strategies turn out to have some common components across asset classes, as shown by Koijen et al. (2012) and Asness, Moskowitz, and Pedersen (2013). While we have compelling stories, both rational and behavioral, of value strategies within equities, bond, and currency markets, we have few theories to link the risk premiums of value strategies across markets. Nevertheless, value is a pervasive factor and theoretically can be implemented cheaply and in size by (p. 235) a large investor. For small investors, there are low-cost index products for value strategies in equity, fixed income, and currency markets as well. The pervasiveness of value across many different asset classes turns out to be something an asset owner should exploit in factor investing, which we come back to in chapter 14.

3.7. Momentum

Another standard investment factor is momentum. This burst onto the academic scene with Jegadeesh and Titman (1993) in the same year that Fama and French were capturing size and value factors. Industry professionals like Richard Driehaus, a star mutual fund manager, had already been practicing momentum for decades. Jegadeesh and Titman (1993) noted that Value Line, a vendor of financial data, has been providing price momentum signals in its publications since the 1980s.

Momentum Investing

Momentum is the strategy of buying stocks that have gone up over the past six (or so) months (winners) and shorting stocks with the lowest returns over the same period (losers). The momentum effect refers to the phenomenon that winner stocks continue to win and losers continue to lose. We call the momentum factor \( WML \), for past winners minus past losers. (It is also called \( UMD \), for stocks that have gone up minus stocks that have gone down.) The momentum strategy, like size and value, is a cross-sectional strategy, meaning that it compares one group of stocks (winners) against another group of stocks (losers) in the cross section, rather than looking at a single stock over time. Winners and losers are always relative—stocks win or lose relative to each other, and the market as a whole can go up or down.
Momentum returns blow size and value out of the water. Figure 7.7, which plots cumulated returns from January 1965 to December 2011, for $SMB$, $HML$, and $WML$ speaks for itself. The cumulated profits on momentum strategies have been an order of magnitude larger than cumulated profits on size and value. Momentum is also observed in every asset class: we observe it in international equities, commodities, government bonds, corporate bonds, industries and sectors, and real estate. In commodities, momentum is synonymous with commodities (p.236) trading advisory funds. Momentum is also called “trend” investing, as in “the trend is your friend.”

Momentum returns are not the opposite of value returns: in Figure 7.7, the correlation of $HML$ with $WML$ is only $-16\%$. But many investors who claim that they are growth investors are actually momentum investors, especially mutual funds (see chapter 16), as pure growth underperforms value in the long run. There is one sense in which momentum is the opposite of value. Value is a negative feedback strategy, where stocks with declining prices eventually fall far enough that they become value stocks. Then value investors buy them when they have fallen enough to have attractive high expected returns. Value investing is inherently stabilizing. Momentum is a positive feedback strategy. Stocks with high past returns are attractive, momentum investors continue buying them, and they continue to go up! Positive feedback strategies are ultimately destabilizing and are thus subject to periodic crashes, as Figure 7.7 shows and as I discuss below.
The presence of momentum does not contradict the advice that I gave on rebalancing in chapter 4 for long-horizon investors. Momentum is primarily a cross-sectional strategy within an asset class: it looks at a particular group of stocks (those with past high returns) relative to another group of stocks (those with past low returns). Rebalancing, in contrast, should be done primarily at the asset class or strategy level because rebalancing requires the assets or strategies to exist over the long run while individual equities can disappear. Momentum manifests across (p.237) asset classes, as does value. It can be part of a long-run investor’s opportunistic strategy (the Merton (1969) long-run hedging demand portfolio).

Momentum is often used as an investment factor, added onto the Fama–French model:34

\[
E(r_t) = \beta_{\text{MKT}} E(r_m - r_t) + \beta_{\text{SMB}} E(\text{SMB}) + \beta_{\text{HML}} E(\text{HML}) + \beta_{\text{WML}} E(\text{WML})
\]

The same intuition applies as with the Fama–French model. The momentum beta, \( \beta_{\text{WML}} \), is centered around zero. Winner stocks have positive momentum betas; their risk premiums are adjusted upward using equation (7.4). Loser stocks have negative momentum betas; their risk premiums are adjusted downward. The market, neither a relative winner nor a relative loser, is simply the market.
Characterizing Momentum Risk

Figure 7.7 shows that despite the large return, on average, of momentum strategies, momentum is prone to periodic crashes. Some of these have lasted for extended periods. Daniel and Moskowitz (2012) examine these in detail. Of the eleven largest momentum crashes, seven occurred during the Great Depression in the 1930s, one occurred in 2001, and the other three occurred during the financial crisis in 2008. The loser stocks then were tanking financials: Citi, Bank of America, Goldman, and Morgan Stanley, and some others hard hit by circumstances, like General Motors. Loser stocks have a tendency to keep losing, and lose they would have, were it not for Uncle Sam riding to their rescue. Government bailouts put a floor underneath the prices of these stocks, and they consequently skyrocketed. Since momentum strategies were short these stocks, momentum investors experienced large losses when these stocks rebounded. It is notable that the other big momentum drawdowns were concentrated during the Great Depression when policymakers also had great influence on asset prices. Momentum seems to reflect monetary policy and government risk during extraordinary times. These have also been times of high volatility.

What else explains momentum? Tantalizing suggestions in the literature suggest that at least some portion of momentum profits correlates with macro factors. Momentum profits, for example, vary over the business cycle and depend on the state of the stock market, and there is a link with liquidity. In the rational story of momentum (which is still far from being fully fleshed out in the literature), asset owners should examine how they behave facing the various sources of macro risk discussed earlier.

The most widely cited theories are behavioral. In the main behavioral theories, momentum arises because of the biased way that investors interpret or act on information. Suppose good news on a stock comes out. Momentum can be generated in two ways. First, investors could have delayed overreaction to this news, causing the price to persistently drift upward. Second, investors could underreact to the news. The price initially goes up, but it does not go up as much as it should have to fully reflect how good the news actually was. Investors then learn and cause the stock to go up again the
next period. Behavioral explanations, then, fall into two camps: momentum is an overreaction phenomenon, or it is an underreaction phenomenon. Distinguishing between these camps is difficult and still bedevils the literature.36

The seminal overreaction models are Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyan (1998). Barberis, Shleifer, and Vishny’s investors suffer from conservatism bias, which causes them to overreact to information because they stick doggedly to their prior beliefs. This causes momentum. In the Daniel, Hirshleifer, and Subrahmanyan model, investors also have psychological biases giving rise to momentum. In this model, investors are overconfident and overestimate their abilities to forecast firms’ future cash flows. They also have biased self-attribution: when they are successful, it must be due to their skill, and when they are unsuccessful, it must be due to bad luck. Informed, overconfident investors (think of retail investors and overconfident hedge fund managers) observe positive signals about some stocks that perform well. These overconfident investors attribute the good performance to their own skill, leading to overconfidence. Based on increased confidence, they overreact and push up the prices of stocks above their fundamental values, generating momentum.

The standard reference for the underreaction theory is Hong and Stein (2000). Hong and Stein rely on “bounded rational” investors who have limited information. Momentum in Hong and Stein’s model is caused by “news watchers” who receive signals of firm value but ignore information in the history of prices. Other investors trade only on past price signals and ignore fundamental information. The information received by the news watchers is received with delay and is only partially incorporated into prices when first revealed to the market. This causes underreaction.

In both the underreaction and overreaction models, prices eventually reverse when they revert to fundamentals in the long run.

**Implications for Asset Owners**

In the context of these behavioral stories, the asset owner should think about what types of psychological biases that she has and how these biases differ from those of the average investor. Do you overreact (or underreact) in a way similar...
Factors

239) to the market? You should also think about how the market’s psychological biases can change. Momentum strategies are negatively skewed; the skewness of the momentum strategy in Figure 7.7 is -1.43. At a minimum, the investor should be able to tolerate large drawdowns induced by momentum strategies. Historically, these declines are concentrated in periods when policymakers have interrupted natural progressions of momentum, as in the Great Depression and the financial crisis.

4. Value Investing Redux
Factor risks represent bad times for an investor. There are two main types of factors—macro factors and investment factors. Assets are exposed to factor risks. The higher the exposure for a factor with a positive risk premium (the higher the asset’s beta), the higher the asset’s expected return.

The value strategy is an example of an investment style factor. In a rational story, value produces losses during bad times, and value stocks are risky. These bad times could coincide with bad times of the economy, as proxied by poor economic growth or poor returns of the market, or they could correspond with bad outcomes of other factors like firm investment. The average investor dislikes these bad times and requires a risk premium to hold value stocks. Thus, value stocks earn high returns to compensate investors for lousy returns during bad times. In behavioral stories, value stocks have high returns because investors underestimate the growth rates of value stocks. They overextrapolate the past growth rates of growth, or glamour, stocks, leading to growth stocks being overpriced and value stocks underpriced. If these behavioral biases are not arbitraged away, value stocks have high excess returns.

In the next two chapters, we turn to characterizing the factor risk-return trade-offs of the bread-and-butter asset classes, equities and fixed income, which can be considered factors in their own right.

Notes:
(1) The data for this strategy, as for all the other Fama-French strategies in this chapter are from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
A very comprehensive study of factor risks is Ilmanen (2011).

The first study to consider macro factors as systematic sources of risk in the cross section of equities was Chen, Roll, and Ross (1986).

A related variable to GDP growth is real consumption growth. It turns out that real consumption is very smooth and actually does not vary much across recessions and expansions, unlike GDP growth. We will look at the effects of consumption risk in chapter 8 when we discuss the equity risk premium.

Deflation, which is not examined here, is also a bad time when assets tend to have low returns.

The VIX index is a measure of option volatilities on the S&P 500 constructed by the Chicago Board Options Exchange. The VIX index captures a variety of risks related to higher movements, including volatility itself, but also jump risk and skewness risk. But the main components captured in the VIX index are volatility and the volatility risk premium.

A term coined by Fischer Black (1976).

See equation (6.2) in chapter 6. For evidence of this time-varying risk premium channel, see Bekaert and Wu (2000).

See, for example, Anderson, Ghysels, and Juergens (2009) for stocks and Ulrich (2011) for bonds.

See Bhansali (2007) and Menkhoff et al. (2012a).
For a negative volatility risk premium in fixed income markets, see Simon (2010) and Mueller, Vedolin, and Yen (2012); currency markets, see Low and Zhang (2005); commodity markets, see Prokopczuk and Wese (2012); and the aggregate stock market, see Bakshi and Kapadia (2003) and Ang et al. (2006). For individual stocks, the volatility risk premium can be positive (some agents really like individual stock risk), see Driessen, Maenhout, and Vilkov (2009). One explanation why individual stocks can carry positive risk premiums but the volatility risk premium is significantly negative at the aggregate level is that much of a stock’s variation is idiosyncratic (see also chapter 10). In portfolios, the stock-specific, idiosyncratic movements are diversified away leaving only market volatility risk, which has a negative risk premium. In the discussion in the main text, volatility risk refers to both “smooth” movements in time-varying volatility (diffusive risk) and abrupt changes (jump risk). More sophisticated models differentiate between the two; see Pan (2002).

Sharpe (2010) calls a non-rebalancing strategy an adaptive allocation policy.

See, for example, Backus and Gregory (1993), Whitelaw (2000), and Ang and Liu (2007).

Available at http://www.frbsf.org/csip/tpf.php.

While most DSGE models do not study how these risks affect asset prices, the newest incarnations of these models, like Rudebusch and Swanson (2012), do.

This is the main economic mechanism in, for example, Geanakoplos, Magill, and Quinzii (2004).

Harvey (2004) finds little evidence, for example, that political risk is reflected in developed countries.

For a recent paper showing how political risk affects equity risk premiums, see Pástor and Veronesi (2012).

The \textit{SMB} and \textit{HML} factors are sometimes given as examples of alternative (or smart) beta. I prefer to use the term dynamic factors because technically beta has the strict
meaning of measuring exposure to a factor, rather than the factor itself. We invest in factor portfolios, not betas.

(20) See Ang and Chen (2002).

(21) SMB, HML, and WML data for Figures 7.6 and 7.7 are from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

(22) Harvey, Liu, and Zhu (2013) examine hundreds of factors explaining stock returns and investigate the effects of data mining on identifying factors.

(23) Schwert (2003), among others, present this argument.


(25) Interestingly, a few authors including Ang and Chen (2007) show that value did not exist in the first half of the twentieth century.

(26) For a labor income risk explanation, see Santos and Veronesi (2006). Parker and Julliard (2005) and Lustig and van Nieuwerburgh (2005) consider luxury consumption and housing risk, respectively. For “long-run” consumption risk, see, for example, Bansal, Dittmar, and Lundblad (2005).

(27) For time-varying betas of value stocks, see Lettau and Ludvigson (2001b), Petkova and Zhang (2005), Lewellen and Nagel (2006), Ang and Chen (2007), and Ang and Kristensen (2012).

(28) This literature was started by McDonald and Siegel (1985).

(29) See chapter 9 for bonds and chapter 11 for commodities. Burnside et al. (2010) develop a disaster-based explanation of the carry trade, similar to the disaster explanations of the equity premium (see chapter 8).

(30) Momentum had appeared in the literature with Levy (1967) but was ignored until Jegadeesh and Titman’s (1993) work.

Factors

(32) See Asness, Moskowitz, and Pedersen (2012) for momentum in equities, government bonds, currencies, and commodities. The standard momentum effect based on past returns is weak in Japanese equities, but versions of momentum do work in Japan; see Chaves (2012). For momentum in corporate bonds and real estate, see Jostova et al. (2013) and Marcato and Key (2005), respectively. Menkhoff et al. (2012b) is a detailed look at momentum in currencies.

(33) See Blitz and Van Vliet (2008).

(34) Carhart (1997) was the first to do this.

(35) See Chordia and Shivakumar (2002), Cooper, Gutierrez, and Hameed (2004), and Pástor and Stambaugh (2003), respectively.

(36) See, for example, Jegadeesh and Titman (2001).

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