Rethinking Expectations

THE WAY FORWARD FOR MACROECONOMICS

Expectations

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Opening Models of Asset Prices and Risk to Nonroutine Change

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6.1 Introduction

Financial markets are, in most respects, prototypes of the markets for which much of contemporary economic analysis was designed. They are characterized by a large number of buyers and sellers; powerful monetary incentives; few, if any, barriers to entry and exit; no impediments to the adjustment of prices; and a plethora of available information that is quickly disseminated around the world. We would expect that financial markets would offer the best opportunity for contemporary economic models to provide explanations of aggregate outcomes. But it is precisely in these markets that contemporary macroeconomic and finance theory has encountered many of its most glaring empirical difficulties.

In Chapter 4 of this volume, we trace contemporary economic theory's empirical and epistemological problems to how it models change in the causal process underpinning market outcomes (see also Frydman and Goldberg 2007, 2011). In financial markets, outcomes are driven primarily by participants' forecasts of prices and risk. As time passes, participants revise their forecasting strategies in ways that they themselves, let alone an economist, cannot fully foresee. Economic policies, institutions, the state of technology, and other features of the social context within which participants make decisions also change in novel ways. Thus, change in financial markets, and in capitalist economies more broadly, is to a significant degree nonroutine, for it cannot be adequately represented in advance with mechanical rules and procedures. Yet the hallmark of contemporary theory is the core premise that an economist can fully specify, in terms of some causal

factors, how individuals alter the way that they make decisions, and how market outcomes unfold over time.

In sharp contrast, we follow an alternative approach to economic analysis—Imperfect Knowledge Economics (IKE). In this chapter, we develop a model of asset prices and risk that has explicit mathematical microfoundations and yet remains open to nonroutine change.[1] At any given point in time, the general structure of our IKE model is no different from that of other macroeconomic and finance models. It consists of representations of individuals' preferences, forecasting behavior, constraints, and decision rules in terms of a set of causal (often called "informational") variables, which portray the influence of economic policy, institutions, and other features of the social context. It also entails an aggregation rule and processes for the informational variables. That participants revise their forecasting strategies, and that the social context changes, at least intermittently, implies that we will need different structures—different specifications of individuals' decisionmaking and the social context—in different time periods. Like other models, the adequacy of an IKE model in accounting for the time-series data hinges on how it characterizes this change.

Most macroeconomists and finance theorists use mechanical rules and procedures that fully prespecify any change in their models' structures. Indeed, nearly all economists construct models that rely on the same structure to represent individual behavior and aggregate outcomes at every point in time. These time-invariant models presume that economic policy and the ways that individuals forecast market outcomes never change. Their key feature is that they represent outcomes in all time periods with a single conditional probability distribution.

To be sure, economists sometimes portray change in their models. However, when they do, they fully prespecify it with deterministic or probabilistic rules that suppose not only that individual decisionmaking or changes in the social context exhibit regularities, but also that these regularities can be adequately characterized with mechanical rules and procedures. As a result, even if they allow for change, these models specify it fully in advance: conditional on the values of the causal variables at a point in time, they determine *exactly* all potential changes and the probabilities with which they might occur—in the past, present, and future all at once. Fully predetermined models represent change as random deviations from a fully predetermined time path and thus assume away nonroutine change altogether.

It was not always so. Early modern economists like Keynes (1921, 1936) and Knight (1921) argued that most business decisions are fraught with "radical uncertainty," a situation in which individual decisions cannot be adequately represented with a standard probability distribution. An extreme version of such uncertainty is often thought to force participants to act according to their "animal spirits," psychological impulses that are largely disconnected from any fundamental considerations that might drive outcomes. However, unless participants' decisionmaking could be connected, at least during some time periods, to the causal factors observable by economists, no formal economic theory with empirical content would be possible.

At the same time, even if one supposes that economic behavior exhibits some regularities, nonroutine change alters how market outcomes unfold over time in ways that put an overarching probabilistic representation of outcomes out of reach of economic analysis. IKE, therefore, stakes out an intermediate position between radical uncertainty, which in its extreme, "animal spirits" version, denies that economists can formulate testable mathematical models of any features of the causal process driving change, and the contemporary presumption that a single conditional probability distribution can adequately represent this process. Although IKE jettisons the presumption that individual decisionmaking and changes in the social context exhibit regularities that conform to fully prespecified rules, it explores the possibility that such behavior nonetheless exhibits regularities. But, at best, we would expect these regularities to be context dependent and qualitative. We would also expect them to be contingent: they begin and cease to be relevant at moments that no one can fully foresee.

In modeling asset prices and risk, an economist's assumptions concerning market participants' forecasting behavior play a crucial role. In searching for empirically relevant regularities that might characterize such behavior, we are guided by empirical findings from behavioral economics and other social sciences. For example, to portray how market participants sometimes revise their forecasting strategies, we make use of psychological findings that indicate that individuals are often slow to revise their beliefs in the face of new evidence. We also build on Keynes's (1936) insight that social conventions are important for understanding how participants form their expectations in financial markets. But our IKE model formalizes these insights with qualitative and contingent conditions, rather than with the mechanical rules that behavioral finance models use to represent behavior.

We also rely on behavioral findings in modeling market participants' risk preferences, drawing on the prospect theory of Kahneman and Tversky (1979). But we use an extension of their original formulation, which we call "endogenous prospect theory," that recognizes that outcomes cannot be represented with an overarching probability distribution.[2]

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1. The analysis in this chapter builds on Frydman and Goldberg (2007, 2008).

2. See Frydman and Goldberg (2007). Kahneman and Tversky (1979) developed their theory for experimental conditions that assume away imperfect knowledge on the part of economists. Subsequent applications of the theory were implemented in fully predetermined models. Endogenous prospect theory extends the applications of the theory to IKE models. It also solves several problems in applying prospect theory to modeling asset markets.

We show that opening a mathematical model to nonroutine change and imperfect knowledge on the part of economists enables us to incorporate both fundamental variables (e.g., earnings and interest rates), on which rational expectations theorists focus, and psychological and social considerations (e.g., confidence and conventions), which behavioral economists emphasize, without presuming obvious irrationality on the part of market participants. We also show that, despite its openness to economists' ever-imperfect knowledge about the process driving change, the model generates implications that can be confronted with time-series evidence.

6.2 Irregular Swings in Asset Prices and Risk

In this chapter, we model market outcomes that contemporary macro-economics and finance theory have found difficult to explain. We focus on the tendency of asset prices to undergo prolonged swings away from and toward estimates of common benchmark levels and on the two-way interdependence of this behavior and financial risk.

Two examples of price fluctuations in asset markets are provided in Figures 6.1 and 6.2, which plot the S&P 500 price index relative to underlying earnings and the British pound–U.S. dollar (BP/$) exchange rate, respectively, along with a common benchmark.[3] The figures show that asset prices can move away from benchmark levels for years at a time. But the instability is bounded: eventually these swings undergo sustained countermovements back toward benchmark values. If prices happen to reach these values, they often overshoot them and begin trending away from the other side. Moreover, although such fluctuations are a recurrent feature of market outcomes, the observed swings are irregular: the magnitude and duration of upswings and downswings vary from one episode to the next in ways that do not seem to follow any consistent pattern. The inability of models based on the Rational Expectations Hypothesis (REH) to account for these features of asset price fluctuations is well known.[4]

The other aggregate regularity that we model involves the market risk premium—the anticipated excess return that market participants in the

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3. The price-earnings (PE) ratio in Figure 6.1 is based on a trailing 10-year moving average of earnings. The data are from Shiller (2000), which are updated on his web site: www.econ.yale/~shiller. The benchmark in the figure is a 20-year moving average of Shiller's PE ratio. The benchmark exchange rate in Figure 6.2 is a purchasing power parity (PPP) rate, which was calculated using the *Big Mac* PPP exchange rate reported in the April 6, 1990, issue of *The Economist* (which was BP1.96/$1) and consumer price index–inflation rate differentials from the IMF's *International Financial Statistics*. Historical averages of PE ratios and PPP exchange rates have long traditions as benchmark values in stock and currency markets, respectively.

4. For stock and currency markets, see Shiller (2003) and Frydman and Goldberg (2007), respectively, and references therein.
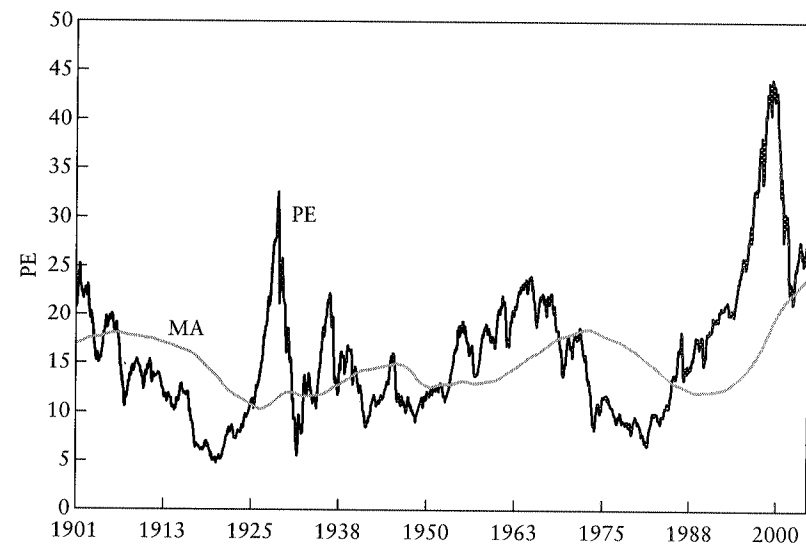

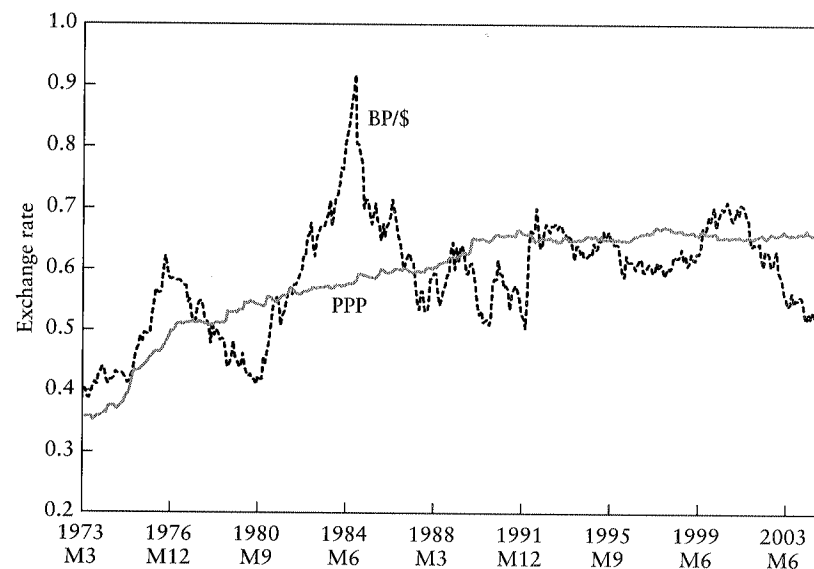**Figure 6.1** S&P 500 stock PE, 1901–2005. MA, moving average; PE, price-earnings ratio.

Figure 6.2 British pound (BP) / U.S. dollar exchange rate, 1973–2005. PPP, purchasing power parity.

aggregate require to hold the available supply of the risky asset. REH risk-premium models relate this premium to the second-moment properties of the data. However, since Mehra and Prescott (1985), economists have known that REH models are grossly inconsistent with time-series data on the market risk premium.

There is much evidence that the market risk premium also undergoes swings and that these fluctuations depend on how the asset price moves relative to benchmark values: as participants bid the price farther away from estimates of benchmark values, it becomes increasingly more risky to gamble on a widening gap. Such behavior can be seen in Figure 6.3, which plots the ex ante excess return on holding U.S. dollar long positions in the BP/$ market and the gap between the exchange rate and its PPP value.[5] The tendency for the market risk premium to move positively with the swing in the exchange rate relative to PPP is striking.

Frydman and Goldberg (2007) and Stillwagon (2012) undertake more formal statistical analyses using parametric and nonparametric procedures and find a positive relationship between the premium and the gap in the three largest currency markets.

As for other asset markets, there is widespread understanding in policymaking circles that risks grow as upswings in equity and housing prices continue for prolonged periods.[6] As the financial crisis that erupted in 2008 dramatically showed, long upswings in these prices are eventually followed by sharp and protracted downswings. Zheng (2009), for example, uses regression analysis to examine the relationship between the premium on stocks over bonds and the gap from benchmark values. Her results are broadly consistent with those for currency markets: the equity premium tends to rise and fall in concert with swings in equity prices relative to the benchmark.

In the remainder of this chapter, we develop microfoundations for an IKE model that can account for the long swings that characterized fluctuations in asset prices and risk—and for the connection between the two—without presuming that individuals forgo obvious profit opportunities.

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5. We use survey data on exchange rate forecasts to measure the market risk premium and the *Big Mac* PPP exchange rate, as in Figure 6.2. The survey data are from Money Market Services International (MMSI), which entail participants' median responses concerning their 4-week-ahead point forecast of the exchange rate. For more details concerning the time plots in Figure 6.3, see Frydman and Goldberg (2007: chapter 12). Other studies that have used MMSI's survey data include Frankel and Froot (1987) and Froot and Frankel (1989).

6. For example, see Borio (2003), Borio and Shim (2007), and Bank for International Settlements (2010). Reinhart and Rogoff (2009) look at data going back as far as eight centuries for 66 countries spanning six continents and find that excessive movements in real exchange rates, real housing prices, and real stock prices are among the top five predictors of subsequent sharp reversals and crises.
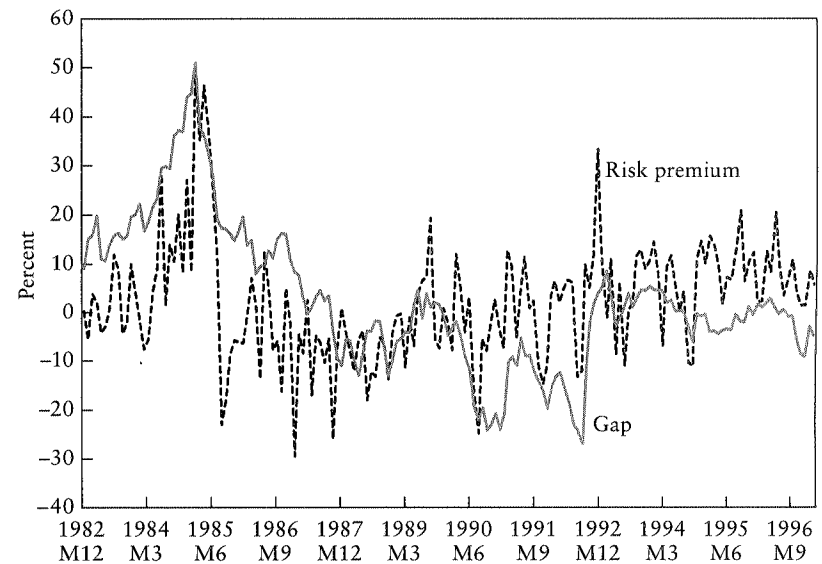
Figure 6.3 British pound (BP) / U.S. dollar risk premium and the gap, 1982–1997.

6.3 Endogenous Prospect Theory of Risk

We portray individual decisionmaking with the usual assumption of utility maximization. But when specifying an individual's preferences and decision rule under uncertainty, we rely on endogenous prospect theory, rather than a standard risk-averse specification and expected utility theory.[7] This alternative specification of preferences and decisionmaking, together with our IKE representation of forecasting, leads to a new model of risk in asset markets: individuals' assessments of the riskiness of holding speculative positions depend on the gap between the asset price and their perceptions of common benchmark levels, rather than on standard measures of volatility.

6.3.1 Individual Preferences

The structure of our model assumes that individuals hold their nonmonetary wealth in a risky and a riskless asset ("stocks" and "bonds," respectively).[8] Individuals can issue bonds and take short positions in stocks without limit,

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7. There is much experimental evidence showing that standard specifications are grossly inconsistent with how individuals actually behave. See Kahneman and Tversky (1979) and Barberis and Thaler (2003) and references therein.

8. In Frydman and Goldberg (2007), we develop the model in the context of currency markets.

although in equilibrium, they must, in the aggregate, hold the available supplies of stocks and outside bonds.

We denote the ex post nominal return on holding a long position in stocks for one period by R_{t+1} and express it using a logarithmic approximation:

$$R_{t+1} = P_{t+1} - P_t - i_t \tag{1}$$

where P_t denotes the logarithm level of the time-t stock price; i_t is the riskless nominal return on bonds; and, for the sake of simplicity, we ignore dividends.[9] Analogously, the one-period return on a short position in stocks is given by $-R_{t+1}$.

An individual's preferences over alternative long and short positions in stocks are specified in terms of gains and losses in wealth relative to some reference level, which Kahneman and Tversky (1979) call "reference dependence." This one-period change in wealth can be written as

$$\Delta^r W_{t+1}^i = W_{t+1}^i - \Gamma_t^i \tag{2}$$

$$= W_t^i \left[a_t^i R_{t+1} + \left(1 + i_t^A - \pi_t \right) \right] - \Gamma_t^i$$

where W_t^i denotes an individual i's nonmonetary real wealth at time t, a_t^i denotes the share of stocks in her portfolio at time t ($a_t^i < 0$ implies a short position), π_t is the nonstochastic rate of inflation, Γ_t^i denotes an individual's reference level, and Δ^r denotes the one-period change in wealth relative to the reference level.[10] When $\Delta^r W_{t+1}^i > 0$ ($\Delta^r W_{t+1}^i < 0$), an individual is said to experience a gain (a loss).

In the context of financial markets, it is natural to set an individual's reference point to the level of wealth she would obtain were she to stay out of the stock market completely:[11]

$$\Gamma_t^i = W_t^i \left(1 + i_t^A - \pi_t \right) \tag{3}$$

Substitution of (3) into (2) yields the following expression for the change in an individual's wealth relative to her reference level:

9. Alternatively, we could redefine P_t to include dividends without changing the main conclusions of our analysis.

10. The real returns on stocks and bonds are $P_{t+1} - P_t + i_t - \pi_t$ and $i_t - \pi_t$, respectively. As such, next-period's wealth is $W_{t+1}^i = W_t^i \left[1 + a_t^i \left(S_{t+1} - S_t + i_t^B - \pi_t \right) + \left(1 - a_t^i \right) \left(i_t^A - \pi_t \right) \right] = W_t^i [a_t^i R_{t+1} + (1 + i_t^A - \pi_t)]$. The assumption of a nonstochastic inflation rate is common in the portfolio-balance literature, because asset prices are considerably more volatile than are goods prices. See Krugman (1981), Frankel (1982), and Dornbusch (1983).

11. In general, however, each individual chooses her own reference level, and neither prospect theory nor available experimental evidence provides guidance as to how an economist should represent it. Other studies that use this reference level in applying prospect theory to modeling asset prices include Barberis et al. (2001) and Barberis and Huang (2001). See Ang et al. (2005) for an extensive discussion of the difficulties inherent in modeling the reference level in the context of prospect theory.

$$\Delta^r W_{t+1}^i = a_t^i W_t^i R_{t+1} \tag{4}$$

A positive realization of R_{t+1}, which we denote by r_{t+1}^+, leads to a gain for an individual who holds a long position (i.e., $a_t^i > 0$) and a loss if she holds a short position (i.e., $a_t^i < 0$). A negative realization of R_{t+1}, which we denote by r_{t+1}^-, leads to the converse. It is common to refer to individuals who hold long and short positions as bulls and bears, respectively.

6.3.1.1 Original Utility Function

In addition to reference dependence, Kahneman's and Tversky's (1979) experimental findings imply that individuals are "loss averse"—their disutility from losses substantially exceeds the utility from gains of the same magnitude. Moreover, their preferences display diminishing sensitivity: their marginal utility of both gains and losses decreases with their size.[12] Tversky and Kahneman (1992) propose a utility function that embodies these characteristics, which we express as

$$V(\Delta^r W) = \begin{cases} (W \, |ar^g|)^\alpha \\ -\lambda (W \, |ar^l|)^\beta \end{cases} \tag{5}$$

where λ is a constant and r^g and r^l denote a gain and loss, respectively, on an open position in stocks. It is convenient to define gains on *both* long and short positions as positive values and losses as negative values:

$$r^g = r_{t+1}^+ \quad \text{and} \quad r^l = r_{t+1}^- \quad \text{if } a > 0 \tag{6}$$

$$r^g = -r_{t+1}^- \quad \text{and} \quad r^l = -r_{t+1}^+ \quad \text{if } a < 0$$

The utility function (5) implies that the degree of loss aversion—defined as the ratio of the disutility of losses to the utility of gains of the same magnitude—depends on the size of an individual's stake in the game, a:[13]

$$\Lambda = \lambda (|ar^l|)^{\beta - \alpha} \tag{7}$$

Like expected utility theory, prospect theory portrays an individual's decisionmaking by assuming that she maximizes a weighted sum of the utilities of single outcomes, called "prospective utility." In the context of our model, an individual chooses a_t^i so as to maximize

12. Diminishing sensitivity implies the familiar concavity of the utility function in the domain of gains. However, in the domain of losses, the utility function is convex, implying that individuals have a greater willingness to gamble as the magnitude of their potential loss rises.

13. This can be seen by rewriting (5) as $V(\Delta^r W) = (W \, |ar^g|)^\alpha - \lambda (W \, |ar^l|)^{\beta - \alpha} (W \, |ar^l|)^\alpha$.

$$PU_t^i = \left|a_t^i W_t^i\right|^\alpha \sum_k^{K^+} \omega_{t,k}^i \left(\hat{r}_{t+1,k}^{g^i}\right)^\alpha - \lambda \left|a_t^i W_t^i\right|^\beta \sum_k^{K^-} \omega_{t,k}^i \left(-\hat{r}_{t+1,k}^{l^i}\right)^\beta \quad (8)$$

where the $\hat{r}_{t+1,k}^{g^i}$s and $\hat{r}_{t+1,k}^{l^i}$s are the possible single gains and losses, respectively, that an individual forecasts; K^+ and K^- denote the numbers of these single outcomes, respectively; and the $\omega_{t,k}^i$s are an individual's decision weights.[14]

6.3.1.2 From Prospective to Expected Values

To derive implications from models based on prospect theory and confront them with time-series data, we must relate individuals' prospective utilities to observable causal variables. Behavioral finance economists address this problem by equating decision weights with probabilities and setting $\alpha = \beta = 1$, thereby assuming that the utility function is linear over potential gains and losses, which enables them to express prospective utility in terms of expected values (e.g., see Barberis et al. 2001).

In the context of our model, these assumptions would imply that

$$PU_t^i = \left|a_t^i W_t^i\right| \left[\hat{r}_{t|t+1}^{i,j} - (1-\lambda)\,\hat{l}_{t|t+1}^{i,j}\right] \quad (9)$$

where $\hat{r}_{t|t+1}^{i,j} = E_t^i[R_{t+1}|Z_t^i] \geq 0$ denotes a bull's ($j = \text{L}$) or bear's ($j = \text{S}$) point forecast of the excess return on holding an open position for one period, which is implied by her forecasting strategy (which we represent by a conditional probability distribution $\mathcal{P}_t^i\left(R_{t+1}\right)$) and the values of the informational variables at time t, Z_t^i. An individual's $\hat{l}_{t|t+1}^{i,j}$ is the conditional expected value of the "loss part" of her distribution of R_{t+1}, which for a bull involves the negative realizations of R_{t+1},

$$\hat{l}_{t|t+1}^{i,\text{L}} = E_t^i[R_{t+1}^\text{L}|R_{t+1}^\text{L} < 0,\ Z_t^i] < 0$$

whereas for a bear, it involves the positive realizations,

$$\hat{l}_{t|t+1}^{i,\text{S}} = E_t^i[R_{t+1}^\text{S}|R_{t+1}^\text{S} < 0,\ Z_t^i] < 0 \quad (10)$$

where $R_{t+1}^\text{L} = P_{t+1} - P_t - i_t$ and $R_{t+1}^\text{S} = i_t + P_t - P_{t+1}$ denote returns on a long and short position, respectively. We refer to $\hat{l}_{t|t+1}^{i,j}$ as an individual's expected potential loss on a unit position.

The specification in (9) implies a risk premium that depends on an individual's degree of loss aversion and her forecast of the potential loss, $(1-\lambda)\,\hat{l}_{t|t+1}^{i,j} > 0$.[15] As long as her expected excess return, $\hat{r}_{t|t+1}^{i,j}$, exceeded

14. We follow Tversky and Kahneman (1992) in assuming a finite set of outcomes.

15. We recall that $\lambda > 1$ and $\hat{l}_{t|t+1}^{i,j} < 0$.

her risk premium, she would want to take an open position in stocks. However, because (9) is linear in the decision variable, a_t^i, she would want to take a speculative position of unlimited size. As it stands, a well-defined equilibrium in which individuals hold diverse forecasts is ruled out.[16]

6.3.1.3 Limits to Speculation and an Individual Uncertainty Premium

In Frydman and Goldberg (2007), we show that the Tversky and Kahneman (1992) utility function implies limits to speculation if one recognizes diminishing sensitivity and sets $\beta > \alpha > 0$. The expression (7) shows that under this assumption, an individual's loss aversion is endogenous, rising as the size of her open position increases and implying the concavity of PU_t^i in a_t^i.[17] However, this nonlinearity creates several problems, including an inability to express the aggregate demand for stocks, $a_t W_t$, in terms of aggregate forecasts, $\hat{r}_{t|t+1}$ and $\hat{l}_{t|t+1}$.[18]

Endogenous prospect theory addresses these problems by reformulating the utility function (5) as

$$V(\Delta^r W) = \begin{cases} (W\,|a|)^\alpha\,|r^g| \\ -\lambda_1(W\,|a|)^\alpha\,|r^l| - \dfrac{\lambda_2}{-\hat{l}_{t|t+1}^{i,j}}(W\,|a|)^{\alpha+1}\,|r^l| \end{cases} \quad (11)$$

where $\lambda_1 > 1$ and $\lambda_2 > 0$ ensure loss aversion. We show in Frydman and Goldberg (2007) that the specification (11) is consistent with all of the main experimental findings of Kahneman and Tversky (1979).[19] And because it implies endogenous loss aversion, it implies limits to speculation.[20]

16. Modeling finite speculative positions, widely called "limits to arbitrage," is viewed as one of the two main pillars of behavioral finance (see Barberis and Thaler 2003). Linearizing the Tversky and Kahneman utility function has led some economists to model finite speculative positions by relying on the assumptions of risk aversion and loss aversion when specifying preferences. The reliance on risk aversion is puzzling, however, given that its rejection in favor of loss aversion has come to be viewed as one of the key findings of behavioral economics. For a review article on modeling limits to arbitrage, see Gromb and Vayanos (2010).

17. We are unaware of any experimental evidence that directly demonstrates a positive relationship between an individual's degree of loss aversion and the size of her stake. But as Myron Scholes emphasized in remarks at the conference "Derivatives 2003: Reports from the Frontiers," held at the Stern School of Business in January 2003, such a relationship accords well with how participants in real-world markets actually behave.

18. Another problem with the specification (5) when $\beta > \alpha > 0$ is that for small position sizes, it violates the basic assumption of loss aversion.

19. This specification implies what we call "endogenous sensitivity": the marginal value of both gains and losses decreases with position size (as it does in Tversky's and Kahneman's original specification), except when the size of the stake becomes large, at which point the marginal value of losses increases with position size. Although Tversky and Kahneman (1992) assume diminishing sensitivity throughout the domain of gains and losses, they recognize in Kahneman and Tversky (1979) that this behavior is typical for smaller gambles, and that increasing sensitivity may characterize individual preferences for larger gambles.

20. The degree of loss aversion is now given by $\Lambda = \lambda_1 + \dfrac{\lambda_2}{-\hat{l}_{t|t+1}^{i,j}} W\,|a|$.

the interest rate on bonds and relative asset supplies. However, to simplify our discussion, we assume that i_t and $\frac{S_t}{W_t}$ are constant and set $i + \lambda_2 \frac{S}{W} = 0$, yielding the following equilibrium condition:

$$\hat{P}_{t|t+1} - P_t = (1 - \lambda_1)\,\hat{l}_{t|t+1} \tag{18}$$

where $\hat{l}_{t|t+1} = \frac{1}{2}\big(\hat{l}^{\mathrm{L}}_{t|t+1} - \hat{l}^{\mathrm{S}}_{t|t+1}\big)$. This simplification enables us to focus on the main drivers of price—movements in individuals' forecasts, $\hat{P}_{t|t+1}$ and $\hat{l}_{t|t+1}$.[27]

6.3.3 Imperfect Knowledge and Expected Values

As time advances, news becomes available about causal variables, and an individual may decide to revise her forecasting strategy, which we represent with a new conditional probability distribution, $\mathcal{P}^i_{t+1}(R_{t+2})$. Both news and a revised forecasting strategy will, in general, lead her to alter her point forecast not only of price but also of the potential unit loss (and thus the riskiness) from holding open positions in stocks. We would not expect such revisions to follow any mechanical rule. But how an individual's $\hat{r}^{i,j}_{t|t+1}$ and $\hat{l}^{i,j}_{t|t+1}$ change from one period to the next may nonetheless exhibit qualitative and contingent regularities. To model this change, therefore, we make use of qualitative and contingent constraints that only partially prespecify it.

This IKE approach enables endogenous prospect theory's specification of risk to address a key concern that other asset market studies applying prospect theory ignore: "[in] the typical situation of choice, where the probabilities of outcomes are not explicitly given[,] . . . the decision weights may be affected by other considerations, such as ambiguity or vagueness" (Kahneman and Tversky 1979: 288–289), which cannot be represented adequately with specific parametric functions of probabilities. These and other considerations arise from the imperfection of knowledge and are what distinguishes decisionmaking in real-world markets from that in experimental settings, where the experimenter fixes the fully prespecified probability distribution that governs the subject's payoffs.

Disregarding the distinction between decision-weighted sums and expected values of outcomes may be unavoidable when applying endogenous prospect theory. However, partially prespecifying change in $\hat{r}^{i,j}_{t|t+1}$ and $\hat{l}^{i,j}_{t|t+1}$ opens the model to the importance of ambiguity and vagueness, and, more generally, to ever-imperfect knowledge in individual decisionmaking.

6.4 An IKE Gap Model of the Market Risk Premium

We turn first to portraying individuals' forecasts of the potential unit loss from speculating with qualitative and contingent constraints and show that the model generates predictions concerning the market risk premium that, although contingent, can be confronted with time-series evidence. We sketch in Section 6.6 how these predictions help explain why protracted price swings away from market participants' estimates of benchmark values are ultimately bounded.

We are guided not only by the empirical record on excess returns discussed in Section 6.2 but also by Keynes's (1936) account of asset markets. Keynes argued that speculators are aware of asset prices' tendency to undergo irregular swings around benchmark levels, and that they take account of this feature of the social context in their attempts to forecast market outcomes. In discussing why an individual might hold cash rather than risky interest-bearing bonds, he observed that "what matters is not the absolute level of [the interest rate] r but the degree of its divergence from what is considered a fairly safe [benchmark] level of r, having regard to those calculations of probability which are being relied on" (Keynes 1936: 201).[28]

Keynes's discussion of the importance of benchmark levels as anchors for asset price swings suggests that market participants look at the gap between the asset price and its benchmark value when forecasting the potential unit loss from speculation. As he put it, "Unless reasons are believed to exist why future experience will be very different from past experience, a . . . rate of interest [much lower than the safe rate] leaves more to fear than to hope, and offers, at the same time, a running yield which is only sufficient to offset a very small measure of fear [of capital loss]" (Keynes 1936: 202).

This insight leads us to relate an individual's expected unit loss on open positions in stocks to her assessment of the gap between the stock price and her perception of the benchmark value:

$$\hat{l}^{i,j}_{t|t+1} = \hat{l}^{i,j}_{t|t+1}\big(\widehat{gap}^i_t\big) \tag{19}$$

where $\widehat{gap}^i_t = P_t - \hat{P}^{i,\mathrm{BM}}_t$, and $\hat{P}^{i,\mathrm{BM}}_t$ denotes an individual's assessment at t of the benchmark stock price.[29]

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28. A benchmark level is, of course, specific to each asset market. Every individual arrives at her own determination of the benchmark value, which implies that, in general, these assessments will differ among individuals. How individuals come to decide on a benchmark level is an open question. Keynes suggests that conventions and the historical record play an important role.

29. The gap could also be defined in terms of an individual's forecast of the next period's asset price (relative to her benchmark value) rather than the asset price itself, or some weighted average of the two, without affecting the conclusions of our analysis. See Frydman and Goldberg (2007).

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27. The variation in interest rates is an order of magnitude or more lower than the variation in stock and currency prices. Consequently, the variations in R_{t+1} and $P_{t+1} - P_t$ are of roughly equal magnitude.

6.4.1 The Gap Effect

Over time, movements in $\widehat{gap}_t^i$ lead an individual to alter her forecast of the potential unit loss, which may involve revisions of her forecasting strategy, $\mathcal{P}_t^i(R_{t+1})$. But, no matter how she might revise her strategy, we suppose that movements of $\hat{l}_{t|t+1}^{i,j}$ are characterized by a "gap effect" that depends on which side of the market she takes.

Consider, for example, an upswing in stock prices that has already climbed above participants' assessments of benchmark levels. A bull forecasts that the price swing will continue, while a bear forecasts the opposite. Nonetheless, both contemplate the potential loss that they would incur if the price were to move against them. If, for example, bulls were to increase their long positions and bid up the price even more, they would also raise their assessments of the potential loss from being wrong: the greater the gap from their estimate of the benchmark, the more concerned they would tend to be about a reversal. In contrast, bears would respond in the opposite way to a further rise in prices: they would tend to become more confident about an eventual reversal, and thus lower their assessments of the potential loss from their short positions.

Of course, how a market participant interprets the gap from benchmark values when assessing risk changes over time in ways that neither she nor an economist can specify fully in advance. Indeed, we present evidence in Frydman and Goldberg (2007, 2011) that the importance individuals attach to the gap when it is historically large is much greater than when it is historically small. No one can fully foresee the thresholds above or below which individuals might consider the magnitude of the gap to be large or small or how the crossing of these thresholds might impact their values of $\hat{l}_{t|t+1}^{i,j}$.

Consequently, we formalize the influence of movements of $\widehat{gap}_t^i$ on $\hat{l}_{t|t+1}^{i,j}$ with qualitative restrictions:[30]

$$\frac{\Delta \hat{l}_{t|t+1}^{i,\mathrm{L}}}{\Delta \widehat{gap}_t^i} < 0 \quad \text{and} \quad \frac{\Delta \hat{l}_{t|t+1}^{i,\mathrm{s}}}{\Delta \widehat{gap}_t^i} > 0 \qquad (20)$$

where Δ is the first-difference operator. These conditions allow for myriad possible nonroutine revisions of an individual's forecasting strategy between

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Depending on the context, an individual's forecast of the potential unit loss may also depend on factors other than the gap. In Frydman and Goldberg (2007), for example, we include current account imbalances as an additional variable in modeling currency risk.

30. The less-than and greater-than inequalities that are used in specifying the gap conditions for a bull and bear follow from defining $\hat{l}_{t|t+1}^{i,\mathrm{L}}$ and $\hat{l}_{t|t+1}^{i,\mathrm{s}}$ as negative values. As such, greater (smaller) losses imply a fall (rise) in $\hat{l}_{t|t+1}^{i,j}$.

successive points in time as $\widehat{gap}_t^i$ changes. They are thus consistent with myriad possible post-change conditional probability distributions, that is, with many $\mathcal{P}_{t+1}^i(R_{t+2})$. But, conditions (20) constrain the set of possible $\mathcal{P}_{t+1}^i(R_{t+2})$s to share a common qualitative feature: they all imply that if the gap were higher at $t + 1$, a bull would forecast a larger potential unit loss (in size) from holding a long position, whereas a bear would forecast a smaller potential unit loss from holding a short position.

The model does not pick out any one of these post-change distributions, so it does not predetermine the exact size of the gap effect over any period. We thus refer to the post-change distributions that are consistent with the gap conditions as "partially predetermined."[31] Any of these partially predetermined $\mathcal{P}_{t+1}^i(R_{t+2})$ distributions represents an individual's forecasting strategy at $t + 1$.

6.4.2 Contingent Predictions of the Market Premium

Restricting change on the individual level with qualitative restrictions implies that our IKE model generates only qualitative predictions on the aggregate level. Equation (19) and the gap conditions (20) imply a partially predetermined specification for the market premium, which we express as

$$\widehat{pr}_{t|t+1} = \sigma_t\left(P_t - \hat{P}_t^{\mathrm{BM}}\right) \qquad (21)$$

where $\sigma_t > 0$, $\hat{P}_t^{\mathrm{BM}}$ is the aggregate of individuals' estimates of the benchmark, and

$$\frac{\Delta \widehat{pr}_{t|t+1}}{\Delta \widehat{gap}_t} > 0 \qquad (22)$$

As on the individual level, the specification (21) and (22) is consistent with myriad possible nonroutine ways that the market premium might change from one point in time to the next; there are many post-change conditional probability distributions on the aggregate level, $\mathcal{P}_{t+1}(R_{t+2})$, at each point in time. However, each of these partially predetermined distributions is characterized by an aggregate gap effect: if the aggregate gap were higher at $t + 1$, it would be associated with a higher market premium.

Consequently, our IKE gap model predicts that $\widehat{pr}_{t|t+1}$ and $\widehat{gap}_t$ will co-vary positively over time. It is thus able to account for this qualitative regularity in time-series data on returns in asset markets. However, it renders no predictions about whether the premium will rise or fall or what the exact size of the gap effect might be in the coming months.

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31. See Chapter 4 (this volume) and Frydman and Goldberg (2008) for a simple algebraic example of partially predetermined probability distributions.

The unfolding of $\widehat{pr}_{t|.t+1}$ over time depends on how P_t moves relative to $\hat{P}_t^{\mathrm{BM}}$, which, as we show in the next section, depends on how individuals' price forecasts unfold in aggregate. The qualitative and contingent restrictions that we use to portray change in $\hat{P}_{t|t+1}$, like the gap restrictions, allow for myriad possible revisions of individuals' forecasting strategies. Partially predetermining change leads to the model's key feature:

- Its predictions concerning whether P_t and $\widehat{pr}_{t|t+1}$ will rise or fall in any one period are contingent on how forecasting strategies unfold.

As we discuss in Section 6.6, this contingency enables the model to recognize the coexistence of both bulls and bears without presuming that either group is obviously irrational.

6.4.3 The Gap Model and Momentary Equilibrium

Portfolio balance and the IKE gap model in (21) and (22) imply the following equilibrium condition for price:

$$P_t = \hat{P}_t^{\mathrm{BM}} + \frac{1}{(1+\sigma_t)}\left(\hat{P}_{t|t+1} - \hat{P}_t^{\mathrm{BM}}\right) \qquad (23)$$

Like most other asset market models, this specification implies that the main driver of price fluctuations in asset markets is individuals' price forecasts. It shows that P_t would undergo a protracted swing away from benchmark values during periods in which $\hat{P}_{t|t+1}$ moved persistently away from these values.[32] This swing would end when the swing in $\hat{P}_{t|t+1}$ ended.

6.5 Bubbles and Lost Fundamentals: Artifacts of the Contemporary Approach

Standard REH models of asset markets suppose that individuals' price forecasts are based on fundamentals, such as corporate earnings and interest rates. The inability of these models to account for the wide price swings in asset markets, and the belief that they provide the right way to portray the importance of fundamentals for rational forecasting, has led economists to develop so-called bubble models. In these models, individuals' price forecasts are driven over the short term not by market fundamentals, but by speculative manias, crowd psychology and other psychological biases, or

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32. We are assuming that any changes in σ_t do not outweigh the impact of a change in $\hat{P}_{t|t+1}$. This assumption is consistent with the qualitative and contingent conditions that we impose on how market participants revise their forecasting strategies. See Section 6.6.3.

technical momentum trading. Such forecasting behavior, which behavioral finance portrays with mechanical rules, leads participants to bid an asset price increasingly away from levels that are consistent with fundamental considerations.[33]

Many point to the long upswing in U.S. equity prices during the 1990s as a prime example of such behavior, and widely refer to this upswing as the "dot.com (or Internet) bubble." During this period, there was indeed much confidence and optimism, and even a sense of euphoria, about Internet stocks, with initial public offerings for many companies witnessing remarkable price increases.[34] At its height in August 2000, the broader S&P 500 price index had climbed to roughly 43 times its underlying smoothed earnings. This eclipsed the market's valuation in October 1929 of 33 times smoothed earnings, which had stood as the market's all-time high until the 1990s.

But, beyond their epistemological flaws (see Chapter 4, this volume), many bubble models are simply inconsistent with the basic features of the price swings that we actually observe in asset markets. According to most of these accounts, prices are supposed to rise steadily, save for occasional random movements in the opposite direction, and when the speculative fever dissipates and the bubble bursts, prices are supposed to jump immediately back to their "known true" fundamental values. However, the long swings shown in Figures 6.1 and 6.2 all involve extended periods (sometimes lasting months), during which the asset price undergoes a persistent, but partial, movement back toward the benchmark. Moreover, the sustained reversals that eventually arise do not involve an immediate return to benchmark values; some last for years at a time and eventually shoot through benchmarks.[35]

6.5.1 Technical Trading and Psychology's Inability to Sustain Swings

To be sure, many participants in markets make use of technical rules, and this trading can contribute to price trends. But the bubble notion's assumption that such considerations alone could sustain an upswing lasting

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33. See Blanchard and Watson (1982) for an early REH bubble model. For seminal behavioral bubble models, see Frankel and Froot (1987) and De Long et al. (1990). More recent models include Abreu and Brunnermeier (2003) and De Grauwe and Grimaldi (2006).

34. Globe.com and eToys, to name just two, saw price rises on the first day of trading of 606% and 280%, respectively. During October 1999, the six largest technology-related companies—Microsoft, Intel, IBM, Cisco, Lucent, and Dell—had a combined market value of $1.65 trillion, or nearly 20% of U.S. GDP.

35. Some behavioral bubble models imply long upswings and downswings, for example, Frankel and Froot (1987). An open question is whether these and learning models (e.g., Mark 2009) can account for the persistence of asset price fluctuations relative to benchmark values.

an entire decade is implausible. Technical trading mostly takes place over minutes or hours. Schulmeister (2003) points out that the technical rules that are used in markets differ in terms of how quickly they generate a buy or sell signal once a price trend has started. This can lead speculators to prolong an initial price trend. However, the trigger times of most technical market strategies differ only in terms of hours or days. Such speculation simply cannot account for long swings lasting many months or years.

Psychological factors, such as confidence and optimism, also influence decisionmaking and no doubt played a role in leading participants in the aggregate to bid up stock prices in the 1990s. But purely psychological accounts of asset markets overlook the possibility that, when forecasting price movements, participants look to fundamental factors that they think will move the market. Moreover, psychological factors themselves are influenced by fundamental considerations. It is simply implausible to suppose that pure crowd psychology could sustain price swings lasting many years. Indeed, any confidence and optimism that might exist in the stock market would quickly evaporate if, say, earnings and overall economic activity consistently moved in the opposite direction.

6.5.1.1 The Fundamental Underpinnings of Psychological and Other Nonfundamental Considerations

Technical and psychological considerations are difficult to measure and incorporate into formal statistical analysis of the determinants of asset price fluctuations. However, using textual data compiled from Bloomberg News' daily "market-wrap" (end-of-day) stories, Mangee (2011) could measure the influence of these considerations, as well as the influence of a wide range of fundamental factors, on daily stock price fluctuations.[36] In writing market-wrap stories, Bloomberg journalists rely on contacts with 100–200 fund managers and other actors directly involved in the markets. Every one of their wrap stories includes at least one direct quote from one or more of these individuals concerning their views about the key factors driving the market. These stories thus provide a window into the decisionmaking of the professional players whose trading determines prices.

Bloomberg journalists indicate that psychological considerations, such as confidence, optimism, and fear, play an important role in daily price fluctuations, having mentioned them as a main driver of prices on 55% of the days in the sample.[37] However, when Mangee (2011) examines the influence of pure psychology—psychological factors that are mentioned separately

36. The study covers January 4, 1993 (Bloomberg's first report) through December 31, 2009.

37. Two excerpts from Bloomberg wrap stories illustrate how psychological factors are reported. In one story (April 21, 2009), a money manager for Pilgrim Investments reports that "IBM earnings are extremely positive . . . this will give confidence and stability to the market."

from fundamentals—he finds that they were mentioned on only 1% of the days.[38]

Bloomberg wrap stories indicate that technical momentum trading also played a relatively minor role in stock price fluctuations. Mangee (2011) finds that this type of trading was mentioned as a main driver of stock prices on only 2% of the days in the sample.[39]

Even when Mangee (2011) combines the influence of pure psychology and momentum trading, there is little support for the bubble view of swings. In virtually no cases do bubble considerations alone move the market. This finding is illustrated in Figure 6.4, which plots the average proportion of days per month that any one of these bubble considerations was mentioned.[40]

The figure shows that bubble considerations had their greatest impact in the second half of the 1990s, providing perhaps some evidence of the bubble view of long upswings. However, these considerations were hardly mentioned at all during much of the 1990s upswing in stock prices. Their importance did rise sharply beginning in 1997. But a high mark of 9% means that they were mentioned on less than 2 of 20 trading days per month on average. Moreover, the importance of bubble considerations began falling rapidly in February 1999. This was a full year before the sharp reversal in equity prices in mid-2000, during the most excessive part of the upswing and exactly when the bubble view would imply that pure psychology and momentum trading should have had their greatest impact. But whatever their impact on prices, these considerations were not the main drivers of the upswing.

Even if one were to view this evidence that psychology and momentum considerations alone do not drive asset price movements as "too soft" to constitute a formal rejection of the bubble view, there is an abundance of

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In another story (March 2, 2009) titled "US Stocks Tumble Trimming Gains at End of Three Week Rally," a money manager observes that "you have got a lot of fear going into earnings."

38. The reporting of pure psychological factors is illustrated by two excerpts from Bloomberg wrap stories. The market wrap on April 21, 1998, cites a chief investment officer for BankBoston, who remarked that "I do think it's mania . . . anytime stocks appreciate 30 to 50 percent in a day, it's the greater fool theory. People think there will always be someone who will pay a higher price." In another story (August 4, 1998), the same investment officer observes that "the selling is feeding on itself . . . people are indifferent about stock prices and valuations. Now they're fearful."

39. The reporting of technical momentum trading is illustrated by two excerpts from Bloomberg wrap stories. The market wrap on January 11, 2001, reports that "the Nasdaq extended gains after 1 pm surging more than 2 percentage points in an hour, as 'momentum' investors, or those who make short term bets on a stock's direction, rushed to buy shares, traders said." In another story (October 4, 2001), a money manager observes that "so-called momentum investors have been buying technology shares because they have to get their foot back in the door and not get left behind."

40. The time plot in Figure 6.4 is based on a 12-month moving average.
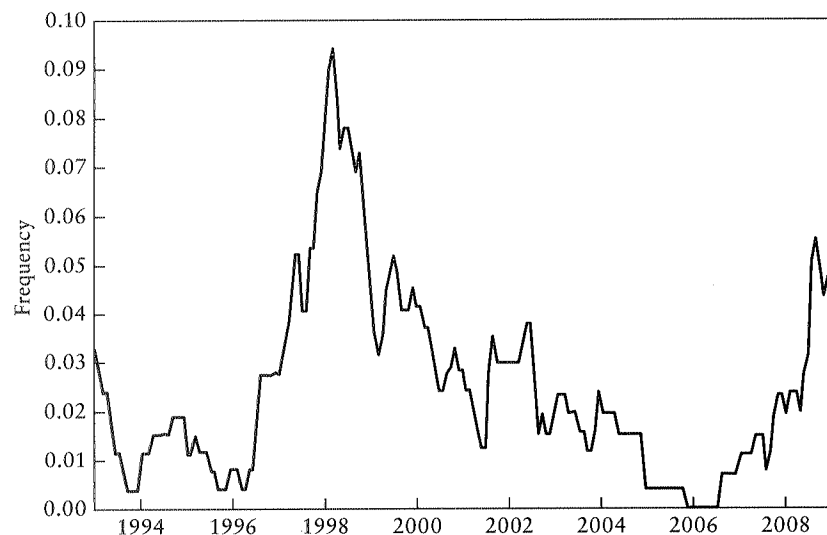
Figure 6.4 Bubble considerations, 1993–2009. The figure shows the average proportion of days per month that Bloomberg wrap stories mentioned a bubble consideration.

Figure 6.5 S&P 500 real stock price and earnings, 1992–2009.

evidence showing the central role that fundamental factors play in asset markets.

6.5.2 Fundamentals Matter, But in Nonroutine Ways

One only has to watch Bloomberg Television or CNBC for a week or two to recognize that news on a wide range of fundamental factors drives prices in major asset markets. As earnings announcements are made or policy developments in Washington, D.C., become known, one sees the markets react. One also sees that the fundamentals that matter change over time in nonroutine ways.

During much of the 1990s, for example, corporate earnings, GDP, employment, exports, productivity levels, and other economic indicators were rising strongly, while inflation rates were declining or holding at benign levels. Free-trade agreements and other political and institutional changes, together with loose monetary policy, were also conducive to growth. As these developments unfolded, they no doubt reinforced confidence and optimism in the widespread view that the U.S. and other economies were in the midst of an information-technology revolution. The bullish trends in fundamental factors, and the greater confidence that they engendered, led many market participants to raise their price forecasts, thereby bidding up stock prices.
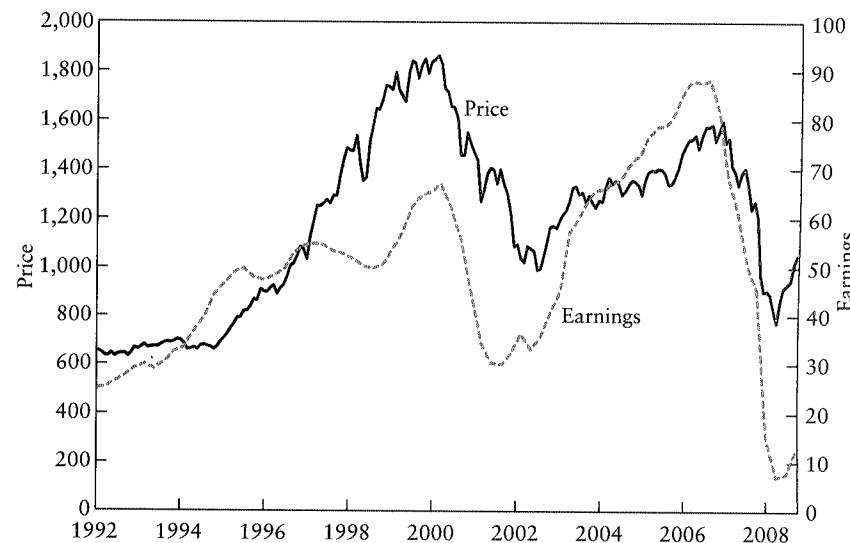
The importance of fundamental factors in driving asset prices is easily seen in Figure 6.5, which plots the S&P 500 price index along with the basket's underlying earnings. The comovement of the two series is striking. Not only do the broad swings in the series rise and fall together, but their major turning points in 2000, 2003, and 2007 are also closely synchronized. The figure belies the bubble view that long upswings in stock prices away from benchmark levels are unrelated to fundamental factors.

Not surprisingly, Bloomberg wrap stories point to the importance of fundamentals in sustaining swings.[41] Mangee's (2011) data show that at least one fundamental factor was mentioned as a driver of stock prices on virtually every day in his sample. The top four broad categories of fundamental considerations were earnings, the economy, interest rates, and sales. A factor in one of these categories was mentioned on 65%, 47%, 38%, and 23% of the days in the sample, respectively.[42]

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41. We again illustrate Bloomberg reporting with excerpts from two of its wrap stories. The story of April 18, 2001, reports that "US stocks rallied after the Federal Reserve surprised investors by cutting interest rates for the fourth time this year." In a story on March 1, 2004, the chairman of Walnut Asset Management observes that "the environment is pretty doggone good for stocks . . . earnings appear to be stronger than anticipated."

42. Mangee's measure of the frequency with which earnings considerations are mentioned by Bloomberg wrap stories includes company announcements of earnings and earnings forecasts. It also includes mentions of stock-price movements that are reported to have arisen because other informational variables, for example, interest rates or sales, led participants to revise their earnings predictions.
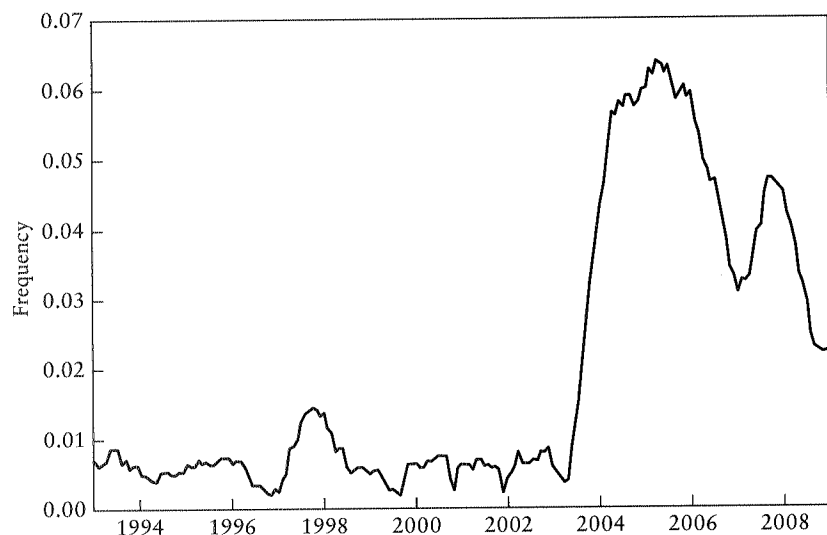
Figure 6.6 Oil price considerations, 1993–2009. The figure shows the average proportion of days per month that Bloomberg wrap stories mentioned oil prices as a major driver of stock prices.

We have argued that the causal process underpinning asset prices changes in nonroutine ways, in part because profit-seeking participants must rely on imperfect knowledge and psychological considerations in revising their forecasting strategies. Bloomberg wrap stories point to this nonroutine change. Indeed, they indicate that the changing nature of the fundamental relationships driving asset markets takes a striking form: different variables matter for prices during different periods. For example, Figure 6.6 plots the average proportion of days per month that oil prices were mentioned as a main driver of stock prices.[43] The figure shows that the market did not pay much attention to the oil price until the end of 2003, when its importance began rising dramatically. By the end of 2004, 60% of each month's wraps mentioned this factor as a driver of the market. No one could have fully foreseen the timing and magnitude of this rise.

Empirical studies that allow for structural change without fully prespecifying it find a similar result. They report that although the causal process driving asset markets changes in non–fully predetermined ways, there are extended periods during which the nonroutine change that does occur is sufficiently moderate that a relatively stable relationship between an asset

43. Again, a 12-month moving average is used.

price and a set of fundamental variables can be estimated. They find not only that fundamental factors matter over the short term, but that different sets of fundamentals matter during different periods.[44] Fully foreseeing when such distinct periods might begin or how long they might last—let alone the precise nature of the fundamental relationships during such periods—is simply beyond anyone's reach.

6.6   An IKE Account of Asset Price Swings

The importance of fundamentals for short-term price movements in asset markets and the central role that individual's price forecasts play in the process (portrayed by (23)) indicate that prolonged price swings stem from trends in fundamentals and how individuals revise the ways that they interpret these trends in thinking about the future. The microfoundations of our account of asset price swings recognize the importance of fundamentals for forecasting and, as before, involve qualitative and contingent restrictions to portray revisions of forecasting strategies.

Market participants' imperfect knowledge and the influence of psychological considerations on their decisionmaking imply that when and how they revise their forecasting strategies do not conform to any mechanical rules. Moreover, a key feature of price swings in asset markets is that they are irregular in duration and magnitude: some swings last for months, whereas others last for years; some involve small departures from benchmark values, whereas others involve large departures. No one can predict precisely when a price swing might begin or end.

To build the microfoundations for a model of this aggregate regularity, we look for regularities on the individual level that are similarly contingent. To portray how individuals revise their strategies for forecasting price, we formalize a qualitative regularity that often, but not always, characterizes behavior. Consequently, our representation is not only qualitative, but also contingent: although the qualitative conditions that we use to portray individual forecasting are assumed to hold most of the time, we do not prespecify the points when they do not. This contingency enables us to account for the unpredictable irregularity of asset price swings and the nonroutine way that fundamentals underpin them. It also allows us to recognize that bulls and bears coexist in the market, and that psychological considerations play a role in decisionmaking, without presuming that individuals forgo obvious profit opportunities.

44. For stock prices, see Mangee (2011), and for exchange rates, see Goldberg and Frydman (1996a,b) and Beckman et al. (2011).

6.6.1 An Individual's Price Forecast

We portray an individual's point forecast of the next period's stock price as

$$\hat{P}^i_{t|t+1} = \beta^i_t Z^i_t \tag{24}$$

where the vector Z^i_t represents the informational variables that individual i uses in forming her price forecast, and β^i_t represents the vector of weights that she attaches to them in thinking about the future.[45] This representation implies that there are two key factors that underpin the evolution of an individual's price forecast over time: revisions of her forecasting strategy—changes in β^i_t, which could include changes in the composition of the set of causal variables Z^i_t—and movements of the informational variables.

6.6.2 Movements of Fundamentals

To illustrate our model of asset price swings, we begin with the assumption that the informational variables in the model follow random walks with constant drifts:[46]

$$\Delta Z^i_t = \mu^i + \epsilon^i_t \tag{25}$$

where μ^i and ϵ^i_t are the vectors of drifts and white-noise errors, respectively. The processes underpinning the unfolding of these fundamentals, of course, depend on economic policy and other features of the social context. Economic policy does change from time to time as new policymakers take charge or as their understanding of economic and social conditions evolves. These conditions themselves also change at times in nonroutine ways. To represent such change in the model we could allow for time-varying drifts in the Z processes in (25). This would enable us to capture the kind of behavior we have already seen in corporate earnings (Figure 6.5): this variable trends in one direction for extended periods, followed by periods in which it trends in the opposite direction.[47]

45. The vector Z^i_t includes expected one-period-ahead changes in informational variables. In this chapter, we simplify by setting these expected changes to constants. A more general IKE model would impose qualitative and contingent constraints on how they unfold over time.

46. To simplify, we assume that the set of information variables does not include the asset price. Recognizing the importance of this variable does not alter the main conclusions of our analysis. See Frydman and Goldberg (2007).

47. In fact, there is much evidence that the processes underpinning many macroeconomic times series are better characterized as involving a persistent drift rather than a constant or no drift, thereby implying near-$I(2)$ behavior. For evidence of such behavior in macroeconomic time series, see Johansen (1997), Kongsted and Nielsen (2004), Juselius (2006), Johansen et al. (2010), and Frydman et al. (2012).

As with market participants' forecasting, we would look for qualitative and contingent regularities in the social context that might help account for the irregular price swings. However, to highlight how IKE representations of forecasting behavior help account for this aggregate regularity, we maintain the assumption of constant drifts for most of this section. We refer to this assumption as a "fixed policy environment."[48]

6.6.3 Nonroutine Revisions of Forecasting Strategies

We recall from the equilibrium condition in (23) that a price swing away from or toward benchmark values arises in the model during any stretch of time in which individuals' price forecasts move persistently away from or toward these values. The swing ends when the swing in $\hat{P}_{t|t+1} - \hat{P}^{BM}_t$ ends. Estimates of common benchmark values, such as those discussed in Section 6.2, move much more slowly than the asset price. Thus, to focus on the central role of price forecasts in driving swings in asset markets, we set the aggregate of individuals' estimates of the benchmark equal to the constant $\hat{P}^{BM}$.[49]

To model revisions of forecasting strategies, we again rely on Keynes's (1936) account of asset markets. This account is often invoked by those who support the view that underlies bubble models, namely, that asset prices are driven by purely psychological considerations. Indeed, Keynes repeatedly alludes to psychological considerations when describing speculation and investment, referring, for example, to the "confidence with which we . . . forecast" (Keynes 1936: 148), "mass psychology" (Keynes 1936: 154), "spontaneous optimism" (Keynes 1936: 161), and "animal spirits" (Keynes 1936: 162).

However, we argue in Frydman and Goldberg (2011) that, although psychological factors undoubtedly played a role in Keynes's thinking about markets, there is much in his *General Theory* to suggest that fundamental considerations were also important to his view of asset price fluctuations. Indeed, he begins his analysis of asset markets by discussing how "expectations of prospective yields" are, in the first place, rooted in individuals' understanding of fundamentals or

knowledge of the facts which will influence the yield of the investment. . . . [The] existing market valuation . . . will only change in proportion to changes in this knowledge. [Keynes 1936: 152]

48. In Section 6.6.6.1, we show how shifts in the policy environment help explain the boundedness of asset price swings.

49. Movements of the imperfectly known benchmark are likely to play a significant role in some markets. However, we focus in this chapter on the fluctuations around benchmark levels.

In using their "knowledge of the facts" to form forecasts, participants

> fall back on what is, in truth, a convention . . . [which] lies in assuming
> that the existing state of affairs will continue indefinitely, except in so far
> as we have specific reasons to expect a change. [Keynes 1936: 152][50]

Keynes's insight that market participants tend to assume that the "existing state of affairs will continue" suggests that they tend to stick with a forecasting strategy for stretches of time. Indeed, it is often unclear whether an individual should alter her strategy. A quarter or two of poor forecasting performance may be the result of random events rather than an indication of a failing strategy. So, unless an individual has "specific reasons to expect a change" in the market, she may leave her current strategy unaltered—even if its performance begins to flag over several periods. Moreover, even armed with "specific reasons to expect a change," it is entirely unclear what new forecasting strategy, if any, she should adopt.

We thus represent how participants tend to alter their thinking about how fundamentals matter with an empirical regularity that we refer to as "guardedly moderate revisions": there are stretches of time during which participants either maintain their strategies or revise them gradually. Such revisions do not generally alter, in substantial ways, the set of fundamentals that participants consider relevant or their interpretation of these fundamentals' influence on future outcomes. As we shall see, all that is needed to sustain a price swing during these time periods is for fundamentals to trend in unchanging ways, which they do quite often.

But, like price swings themselves, the tendency toward guardedly moderate revisions is a qualitative regularity that occurs in contingent ways. There are occasions when news about fundamentals and price movements leads participants to revise their forecasting strategies in nonmoderate ways. Such revisions can have a dramatic impact on price and spell the end of a price swing in one direction and the start of a new swing in the opposite direction.

6.6.3.1 Formalization of Guardedly Moderate Revisions

To formalize the contingent regularity of guardedly moderate revisions, we need to define a baseline against which revisions may be judged to be either moderate or nonmoderate. We note that as trends in fundamentals unfold, an individual would, in general, alter her price forecast even if she were to keep her forecasting strategy unchanged. The drift underpinning this change in the status quo of $\hat{P}^i_{t|t+1}$ serves as our baseline for judging whether revisions are guardedly moderate.

50. By "existing state of affairs," Keynes means "knowledge of the facts."

Given the representations in (24) and (25), the total change in an individual's price forecast can be expressed as

$$\hat{P}^i_{t|t+1} - \hat{P}^i_{t-1|t} = T\hat{P}^i_{t|t+1} + \epsilon^i_t \tag{26}$$

where $T\hat{P}^i_{t|t+1}$ is the "trend change" in the individual's forecast between $t-1$ and t:

$$T\hat{P}^i_{t|t+1} = \Delta\beta^i_t Z^i_t + \beta^i_{t-1}\mu^{Z^i} \tag{27}$$

This trend change depends on how an individual revises her forecasting strategy, $\Delta\beta^i_t$, and on what we call the "baseline drift" in her point forecast, $\beta^i_{t-1}\mu^{Z^i}$.[51] The baseline drift represents the change that would result if an individual were to use the same forecasting strategy at $t-1$ and t and if the only change in her price forecast at t resulted from drifts in fundamentals. If she were to refrain from revising her strategy over the next T points in time, $T\hat{P}^i_{t|t+1}$ would again be equal to $\beta^i_{t-1}\mu^{Z^i}$ between each of these points. During this stretch of time, $\hat{P}^i_{t|t+1}$ would tend to move in one direction, which would be determined by the algebraic sign of the baseline drift.

Suppose, for example, that an individual's $\beta^i_{t-1}\mu^{Z^i}$ was positive. In this case, movements in fundamentals would, on average, lead her to raise her price forecast between $t-1$ and $t+T$.

Of course, movements in fundamentals may lead an individual to revise her forecasting strategy at any point during this stretch of time. To see how this works in our model, consider such a revision at t, which is portrayed by a new set of parameters, $\beta^i_t \neq \beta^i_{t-1}$. The impact of the new parameters on the price forecast at t is $\Delta\beta^i_t Z^i_t$. But the revision also gives rise to a new baseline drift, $\beta^i_t \mu^{Z^i}$, which portrays how trends in fundamentals influence the individual's forecast in the next period, $t+1$.

Each of these effects on the price forecast—$\Delta\beta^i_t Z^i_t$ at t and $\beta^i_t \mu^{Z^i}$ at $t+1$—could reinforce or impede the influence of the initial baseline drift, $\beta^i_{t-1}\mu^{Z^i}$, which in our example is positive. The new β^i_t would be reinforcing at t and $t+1$ if $\Delta\beta^i_t Z^i_t > 0$ and $\beta^i_t \mu^{Z^i} > \beta^i_{t-1}\mu^{Z^i}$. In this case, the revision at t would add to the initial influence of fundamentals and contribute to a higher $\hat{P}^i_{t|t+1}$ at t and a faster growing $\hat{P}^i_{t|t+1}$ at $t+1$.

51. To portray change in the set of fundamentals that an individual might use to form her price forecast, we suppose that the vector Z^i_t represents at every point in time all possible fundamentals that she might use. If, for example, an individual uses a particular variable Z^i_j to form her forecast at t but not at $t-1$, then $\beta^i_{j,t-1} = 0$ and $\Delta\beta^i_{j,t} = \beta^i_{j,t}$.

If, however, the new β_t^i was impeding at t and $t + 1$—$\Delta\beta_t^i Z_t^i < 0$ and $\beta_t^i \mu^{Z^i} < \beta_{t-1}^i \mu^{Z^i}$—it would subtract from the positive influence of fundamentals at t and lead to a lower baseline drift at $t + 1$. The size of these effects could be large enough that, although the initial influence of fundamentals was positive, $\hat{P}_{t|t+1}^i$ fell at t and $t + 1$.

But, regardless of whether revisions were reinforcing or impeding between $t - 1$ and $t + T$, if their effects on an individual's price forecast and baseline drift were moderate enough throughout this period, the trends in fundamentals would still tend to dominate and lead her to raise her price forecast in one direction.

This reasoning underpins our formalization of guardedly moderate revisions, which involves two qualitative conditions,

$$\left|\Delta\beta_t^i Z_t^i\right| < \delta_t^i \tag{28}$$

$$\left|\Delta\beta_t^i \mu^{Z^i}\right| < \delta_t^i \tag{29}$$

where $|\cdot|$ denotes absolute value, and $\delta_t^i = \left|\beta_{t-1}^i \mu^{Z^i}\right|$ is the magnitude of the baseline drift. The first condition constrains revisions at t so that the impact of movements in fundamentals on an individual's price forecast tends to outweigh the impact from revisions. The second condition also constrains revisions at t and implies that the sign of the baseline drift does not change. Consequently, if these conditions were to characterize how an individual revised her forecasting strategy over a stretch of time, and trends in fundamentals remained unchanged over that time, she would tend to alter her price forecast in one direction or the other.

The qualitative constraints (28) and (29) embody the idea that unless an individual has "specific reasons to expect a change" in the "existing state of affairs," she tends to maintain her forecasting strategy or, if she revises it, to do so in ways that would not have a large impact on her price forecast or its baseline drift. Because they restrict neither the causal variables that may enter (24) nor how exactly these variables might matter, these constraints leave room for non–rule based revisions. Moreover, they do not imply that the change in an individual's price forecast must be small: our model's constraints are compatible with large changes in $\hat{P}_{t|t+1}^i$ that result from large movements in fundamentals.

6.6.3.2 Psychological Motivation for Guardedly Moderate Revisions?

Although we find compelling Keynes's insight that individuals fall back on the assumption that the "existing state of affairs will continue," we are unaware of any direct empirical evidence that would support this claim. To be sure, psychologists have uncovered experimental evidence of a regularity that they call "conservatism": when individuals change their forecasts about

uncertain outcomes, they tend to do so gradually, relative to some baseline—a finding that is consistent with our characterization of guardedly moderate revisions (see Edwards 1968; Shleifer 2000; and references therein). But it is a finding that pertains to how an individual alters her *forecast* rather than to how she might revise her forecasting *strategy*.

Even if we were to formulate conservatism as a qualitative regularity, it would imply a restriction on an individual's forecasting behavior that was stronger than our guardedly moderate restrictions. For example, suppose that an individual kept her forecasting strategy unchanged between two consecutive points in time, but increased her price forecast nonetheless because of movements in fundamentals. Conservatism would restrict the size of the impact on $\hat{P}_{t|t+1}^i$, whereas our guardedly moderate conditions would not.

Moreover, because behavioral economists insist on sharp predictions, they characterize conservatism not as a qualitative regularity but as a mechanical one. As a result, existing formulations of conservatism imply restrictions on individual behavior that are much stronger than our representation of guardedly moderate revisions. These fully predetermined representations presume that individuals underreact to new information in a fixed way relative to what an economist's overarching probability model would imply. They thus imply that individuals never revise their forecasting strategies (e.g., see Barberis et al. 1998).

6.6.4 Irregular Swings in an Individual's Price Forecast

Market participants' tendency to deal with uncertainty by keeping forecasting strategies unaltered or revising them in guardedly moderate ways is a *contingent* regularity: it characterizes behavior during stretches of time that begin and end at moments that no one can predict. Eventually, the "existing state of affairs" changes or an individual has "specific reasons to expect" such a change. Even if trends in fundamentals continued in the same broad directions, the qualitative regularity of guardedly moderate revisions may cease to hold at unpredictable moments.

Consequently, our IKE representation does not restrict an individual's forecasting behavior to be consistent with conditions (28) and (29) at every point in time. Moreover, it does not prespecify the stretches of time during which they characterize behavior, that is, when these stretches might begin or end. Because of this contingency, our model implies that an individual's price forecast will undergo swings of irregular duration and magnitude.

To see this, consider a stretch of time from $t - 1$ to $t + T$, during which trends in fundamentals remained unchanged and an individual's initial interpretations of these trends would, in the absence of any revisions of her strategy, lead her to raise her price forecast. If, during this stretch, revisions of her strategy could be characterized as guardedly moderate, her price forecast would tend to rise over the period. An end to this upswing in $\hat{P}_{t|t+1}^i$

would occur at $t + T + 1$, if her revisions were impeding and nonmoderate—that is, *not* characterized by the conditions (28) and (29). Such drastic revisions would have a greater impact on her price forecast than the impact from the drifts in fundamentals, and so $\hat{P}^i_{t|t+1}$ would tend to fall at $t + T + 1$. Moreover, nonmoderate and impeding revisions would lead to a switch in the sign of the baseline drift, so that the influence of these drifts on the individual's price forecast in the next period, $\beta^i_{t+T+1}\mu^{Z^i}$, would be downward. The fall in $\hat{P}^i_{t|t+1}$ would then tend to continue if revisions of the individual's strategy were once again characterized as guardedly moderate for another stretch of time beyond $t + T + 1$.

The downswing in $\hat{P}^i_{t|t+1}$ would continue until the individual once again decided to revise her strategy in a dramatic and impeding fashion. At such times, her forecast would experience another reversal, which might or might not turn into a sustained countermovement.

6.6.5   Bulls, Bears, and Irregular Swings in the Aggregate Forecast

There are, of course, stark differences in bulls' and bears' strategies; after all, one group forecasts a rise in price, whereas the other forecasts a decline. However, because our characterization of guardedly moderate revisions is qualitative and contingent, it is open to nonroutine changes in bulls' and bears' forecasting strategies and is consistent with the myriad diverse ways in which this change occurs. Regardless of the precise way in which a participant revised her strategy, or whether she was a bull or a bear, her price forecast would tend to move in one direction or the other for as long as her revisions continued to be guardedly moderate and trends in fundamentals remained unchanged.

The equilibrium condition (23) shows that what matters for asset prices is how the aggregate of participants' diverse price forecasts moves over time. Even if all participants were assumed to revise their strategies in guardedly moderate ways over a stretch of time, this would not, in general, imply that the aggregate forecasting strategy was also characterized by guardedly moderate revisions.

To connect the implications of our representation of individual behavior to aggregate outcomes, we rely on assumptions concerning the degree to which qualitative interpretations of movements in fundamentals vary across individuals. This variation implies another layer of contingency to our IKE model's predictions.

6.6.5.1   Moving to the Aggregate Level

To see what assumptions about diversity are needed for our model to generate predictions on the aggregate level, we initially consider a stretch of time, t to $t + T$, during which the drifts in fundamentals remain unchanged

and all participants revise their forecasting strategies in guardedly moderate ways. Participants who are bulls at t predict a higher price at $t + 1$,

$$\hat{P}^{i,\text{L}}_{t|t+1} - P_t > 0 \tag{30}$$

whereas those who are bears predict a lower price,

$$\hat{P}^{i,\text{S}}_{t|t+1} - P_t < 0 \tag{31}$$

But, regardless of whether they are bulls or bears at t, we know from Section 6.6.3.1 that all the individual $\hat{P}^i_{t|t+1}$ values in our example move in one direction or the other, on average, between t and $t + T$.

Whether an individual's price forecast rises or falls over the period depends on how the trends in fundamentals initially impact her forecast, which we portray by the initial baseline drift. If, for example, the initial impact is positive ($\beta^i_{t-1}\mu^{Z^i} > 0$), all subsequent trend changes in an individual's forecast will be positive ($\mathcal{T}\hat{P}^i_{t|t+1} > 0$), and she will tend to raise $\hat{P}^i_{t|t+1}$ over the period. We note that such an upswing in $\hat{P}^i_{t|t+1}$ could characterize an individual who is a bear throughout the period. Although a bear's interpretation of fundamentals implies $\hat{P}^i_{t|t+1} < P_t$, movements in fundamentals—say, a rise in overall economic activity—could well lead her to increase $\hat{P}^i_{t|t+1}$, thereby becoming less bearish over time.

In the aggregate, the trend change in $\hat{P}_{t|t+1}$ at each point in time is a weighted average of the individual values of $\mathcal{T}\hat{P}^i_{t|t+1}$ given by (27):

$$\mathcal{T}\hat{P}_{t|t+1} = \sum_i \omega^i \left(\Delta\beta^i_t Z^i_t + \beta^i_{t-1}\mu^{Z^i} \right) \tag{32}$$

where the aggregation weights, as before, are based on wealth shares and are assumed to be constant. It is immediately clear that if trends in fundamentals and guardedly moderate revisions led all individuals to alter their price forecasts in the same direction between t and $t + T$, the aggregate $\hat{P}_{t|t+1}$ would also undergo a swing.

To be sure, knowledge is imperfect, and some market participants will interpret movements in certain fundamentals positively, whereas others will view them negatively. Whether $\hat{P}_{t|t+1}$ tends to move in one direction between t and $t + T$ in our example would then depend on the degree to which participants interpret movements of fundamentals in a qualitatively similar way. This diversity of qualitative interpretations varies over time in ways that no one can fully foresee. However, if it remained sufficiently small, the constant trends in fundamentals and guardedly moderate revisions on the individual level would lead most participants to alter their price

forecasts in one direction over the period. Moreover, these swings in individual $\hat{P}^i_{t|t+1}$ values would be associated with a swing in $\hat{P}_{t|t+1}$ in the same direction.

In what follows, we impose this constraint on the variation in diversity as long as asset price departures from estimates of the benchmark value are below a threshold level. Indeed, in most markets, participants tend to interpret many of the fundamentals that drive forecasts in a qualitatively similar way. For example, in the stock market, positive trends in overall economic activity, earnings, sales, and employment are widely viewed by participants as reasons to raise their price forecasts regardless of whether they are bulls or bears, whereas rising interest rates and oil prices have the opposite effect.

However, we would expect diversity in the market to grow if stock prices moved, for example, far above estimates of benchmark values. Participants know that such departures are eventually reversed, although no one knows when the reversal will begin. Even when valuations become high, some participants continue to forecast that the upswing will persist over the next period, while others predict a reversal. Rising earnings and economic activity may lead both bulls and bears to raise their price forecasts, but at some point, even these trends would not be interpreted in qualitatively similar ways as bears began to gain greater confidence in a reversal and stopped raising their forecasts $\hat{P}^i_{t|t+1}$. As we discuss in more detail in the next section, this growth in diversity can spell the end of a price swing.

The assumption that all market participants revise their strategies in guardedly moderate ways is strong. At each point in time we would expect that the forecasting behavior of some participants could be characterized as guardedly moderate, while that of others could not. Whether the aggregate forecast tends to move in one direction between t and $t + T$ in our example depends on the relative weight of the participants in the market whose revisions are guardedly moderate. A swing would arise during the period if this weight remained sufficiently high.

6.6.6 *Irregular Price Swings*

As long as departures of the asset price from estimates of benchmark values remain below some unknown threshold, the model does not prespecify the stretches of time during which market participants, on the whole, revise their forecasting strategies in guardedly moderate ways. Therefore, it does not prespecify when swings in the aggregate price forecast, $\hat{P}_{t|t+1}$, and thus in the asset price, will begin or end.

Participants' decisions to revise their strategies depend on many considerations, including their current strategy's performance, whether they have "specific reasons to expect a change" in how fundamental factors are trending or how they are influencing prices, and the "confidence with which

we . . . forecast" (Keynes 1936: 148). Nonmoderate and impeding revisions of forecasting strategies are often proximate to points at which trends in fundamentals also reverse or there is a major change in economic policies or institutions. At such points, the market undergoes a price reversal. But once such changes have occurred and have been interpreted, individuals are likely to resume revising their strategies in guardedly moderate ways: they would tend to keep their forecasting strategies unchanged or revise them only moderately, but they would always be on guard for change. In that case, and if fundamentals trended in persistent directions, the asset price would begin trending in the other direction for another stretch of time.

The new price swing would continue until participants again lost confidence that the new trends in fundamentals would persist, or some other change in the existing state of affairs led them to revise their strategies in a nonmoderate and impeding fashion. At such times, the asset price would experience another reversal, which might or might not turn into a sustained countermovement.

6.6.6.1 Risk and Bounded Instability

Although our model does not fully prespecify when asset price swings begin or end, it does imply that swings away from estimates of benchmark values eventually end and are followed by sustained countermovements back toward these values. This implication follows from our account of risk and assumptions about the unfolding of diversity.

As an asset price rises well above or falls well below most participants' perceptions of benchmark values, those who are betting on further movements away from these levels raise their assessments of the riskiness of doing so. Eventually, these assessments lead them to revise their forecasting strategies in nonmoderate and nonreinforcing ways. When that happens, even the most excessive price swings come to an end and are followed by sustained reversals back toward benchmark levels.

Consider a stretch of time during which market participants revise their forecasting strategies in guardedly moderate ways. A bull forecasts that the price swing will continue over the near term, whereas a bear forecasts the opposite. However, our assumption about diversity implies that as long as the asset price does not depart too far from benchmark values, most bulls and bears would interpret movements in fundamentals in qualitatively similar ways. Suppose, initially, that the mix of forecasting strategies and drifts in fundamentals leads both bulls and bears to raise their price forecasts over time; that is, the baseline drifts for both groups, $\beta^{i,L}_{\tau-1}\mu^{z^{i,L}}$ and $\beta^{i,S}_{\tau-1}\mu^{z^{i,S}}$, are positive. These developments would lead bulls to become more bullish and bears to become less bearish. During this stretch of time, then, $\hat{P}_{t|t+1}$ and P_t, would tend to rise, say, farther above most estimates of benchmark levels.

But, although bulls expect a greater return, they understand that such upswings eventually end, so they increase their assessment of the risk of

a reversal and capital losses. The resulting rise in their premiums tempers their desire to increase their speculative positions. If trends in fundamentals continued, thereby prolonging the excessive price swing, a threshold would eventually be reached at which bulls would become so concerned about a reversal that they would no longer revise their forecasting strategies in guardedly moderate ways. At that point, they would either reduce their long positions or abandon them altogether, precipitating a price reversal.

Bears also understand that upswings eventually end, which is why they also change their premiums, but in the opposite direction. If the upswing continued, they would eventually cease to interpret trends in fundamentals as reasons to raise their price forecasts. But this would imply that they revised their forecasting strategies in nonmoderate and impeding ways, likewise contributing to the self-limiting nature of long swings away from benchmark levels.

When, precisely, the gap from benchmark levels is perceived to be too large for bulls and bears to continue to revise their strategies in guardedly moderate ways depends on many factors, including economic, political, and policy considerations that no one can fully prespecify. Thus, no one can foresee when long swings away from benchmark levels will eventually end.

In currency markets, policymakers use such benchmarks as PPP to set economic policy, and their actions play an important role in keeping exchange rate swings bounded. The empirical record shows that policy officials eventually become concerned about large departures in the exchange rate from PPP and alter policy to engender a reversal.[52] As with revisions of forecasting strategies, we would not expect that such policy changes would follow any mechanical rule. But the proximity of major reversals in currency markets to major changes in policy suggests that policymakers play an important role in keeping long swings in currency markets bounded.[53]

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52. Examples of such behavior include the coordinated interventions by central banks and the changes in monetary and fiscal policies that were aimed at bringing down U.S. dollar exchange rates in 1985 and yen exchange rates in 1995, as well as the interventions by the U.S. Federal Reserve and the European Central Bank to stem the dollar's fall in 2007 and the first half of 2008.

53. For example, the major reversals in U.S. dollar exchange rates in late 1979 and early 1985 were associated with the arrival of Paul Volcker and James Baker, respectively, both of whom quickly engineered major changes in policy. An example of a connection between policy and major reversals in other asset markets is provided by the downturn in U.S. equity markets that began in August 2000, which came on the heels of the Federal Reserve's decision to raise the federal funds rate from 4.74% in July 1999 to 6.5% in May 2000. Beyond the policy channel, departures in asset prices from benchmark values endogenously influence trends in macroeconomic fundamentals in ways that also keep asset price swings bounded. For example, swings in exchange rates eventually lead to changes in current account imbalances and economic growth that tend to limit such swings.

6.7 Contingent Predictions of Long Swings and Their Compatibility with Rationality

Despite its contingent character and openness to nonroutine change, our representation of bulls' and bears' decisionmaking and assumptions about diversity place sufficient structure on the analysis to account for the basic features of asset price swings depicted in Figures 6.1 and 6.2.

The qualitative conditions formalizing guardedly moderate revisions and our assumptions about diversity do not produce sharp predictions about asset price fluctuations. Instead, they are consistent with myriad possible changes in β_t and the composition of Z_t between two consecutive points in time. At any point in time, therefore, they imply myriad post-change probability distributions for price—one for each possible value of β_t—conditional on any of the distributions at time $t - 1$ and the processes underpinning fundamentals. However, each of these partially predetermined distributions implies that the price would tend to move in one direction or the other over time if the drifts underpinning fundamentals remained unchanged.

Our IKE model predicts, therefore, that price swings in asset markets will occur during stretches of time in which trends in market fundamentals are persistent, and participants, on the whole, interpret the impact of these trends on their price forecasts in a qualitatively similar manner and revise their strategies in guardedly moderate ways. The uncertainties inherent in forecasting asset prices, as well as findings in psychology, suggest that participants often stick with a strategy for stretches of time and that when they do revise their strategies, they are reluctant to do so in dramatic ways. Moreover, macroeconomic fundamentals often trend in particular directions for years at a time. Given these qualitative regularities in individual forecasting and the social context, our IKE model predicts that asset prices quite often will undergo swings either away from or toward estimates of benchmark values. If a price swing is headed toward benchmark values and the qualitative conditions for a swing endure (which they often do), the asset price will eventually shoot through the benchmark and begin trending away from the other side. Moreover, participants' use of the gap from benchmark levels to assess the riskiness of their speculative positions implies that long swings away from these levels cannot last forever. Eventually, conditions in the market change, and a sustained reversal results.

The contingent nature of its representation on the individual level implies that the model renders no prediction of whether the asset price will rise or fall in any given period. The trends in fundamentals could reverse directions at any time, and participants may cease to interpret these trends in a qualitatively similar manner or decide to revise their strategies in nonguardedly moderate ways at any time. Consequently, at each point in time, the model is consistent with many partially predetermined probability distributions that

imply a tendency for the asset price to move in the same direction during some period and with many others that imply a tendency for it to move in the opposite direction during the same period.

The model is thus compatible with the coexistence of both bulls and bears. At each point in time, it is reasonable for some participants to expect the price to rise and for others to expect it to fall. It may even be reasonable for some individuals to remain consistently bullish or bearish during a period in which the asset price moves steadily against them. Indeed, an individual might reasonably decide to increase the size of her long or short position precisely *because* the price has moved farther away from her expected level.

6.8 An Intermediate View of Markets and the Role of the State

Our IKE model enables us to uncover the importance of both fundamentals and psychological considerations for understanding price swings and risk in financial markets without presuming that market participants forgo obvious profit opportunities. In Frydman and Goldberg (2009, 2011), we show how this model leads to an intermediate view of asset price swings away from and back toward benchmark values: they play an integral role in the process by which financial markets evaluate prior investments and foster new companies and projects—the key to modern economies' dynamism. And yet, owing to the imperfection of knowledge, these swings can sometimes become excessive, exacting huge economic and social costs.

This intermediate view contrasts sharply with the polarized positions that are implied by fully predetermined models of macroeconomics and finance: asset price swings are based either on "rational" decisionmaking that enables society to allocate its scarce capital nearly perfectly or on crowd psychology and technical trading that allocates capital haphazardly.

Our intermediate view of markets not only sheds new light on the supposed empirical puzzles implied by fully predetermined models; it also leads to a new way of thinking about the relationship between the market and the state. Because asset price swings away from benchmark values can sometimes become excessive, there is a role for the state to stand guard and dampen this excess. Our IKE model implies new channels for policy officials to accomplish this task and supplies new tools with which regulators can assess systemic and other financial sector risks.

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