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The puzzle of long swings in equity markets: Which way forward?

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THE PUZZLE OF LONG SWINGS IN EQUITY MARKETS:
WHICH WAY FORWARD?

BY

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DISSERTATION

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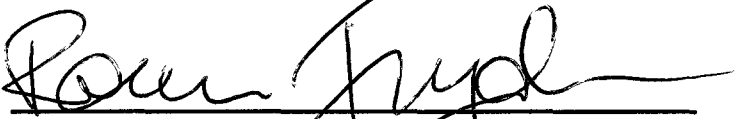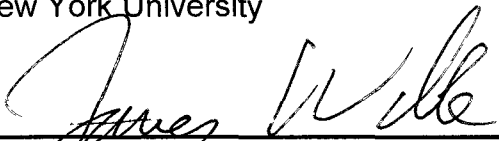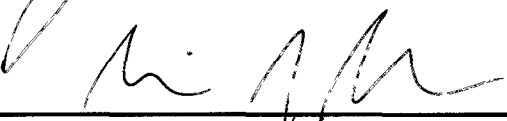
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DEDICATION

This thesis is dedicated to my amazing wife Laurin. You have been an enduring source of fortitude when it was needed most. Your love and support have seemed endless. You have been my shining star and a source of inspiration throughout this journey. Your infinite and enduring patience and understanding have made all the difference in the world. I will, with all my love, make it up to you.

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ABSTRACT

THE PUZZLE OF LONG SWINGS IN EQUITY MARKETS: WHICH WAY FORWARD?

by

Nicholas J. Mangee

University of New Hampshire, September, 2011

The main purpose of this dissertation is to determine which class of models – bubble or Imperfect Knowledge Economics (IKE) – provides the better account of short-term stock price fluctuations – and thus long-swings – on the basis of empirical evidence. However, it is not clear how to test the bubble models' implication that pure psychological and technical momentum-related factors are the primary driver of stock price movements. Moreover, IKE models' implication that fundamentals are the primary drivers of stock price movements – but that changes in this relation are non-routine – is also problematic.

This thesis addresses these difficulties in two main ways. One is to construct a novel dataset based on *Bloomberg News'* end-of-the-day equity market wrap stories. The textual data provides unambiguous support for IKE models over the bubble models. They indicate that fundamental factors are the primary driver of price fluctuations and that this relation changes at times and in ways that would be difficult to adequately capture with any overarching rule. Psychological considerations are also found to be quite important, but their impact is almost always tethered to a fundamental factor. The bubble models'

implication that pure psychological and technical momentum-related considerations are the main drivers of stock prices receives little support.

The thesis also relies on formal econometric analysis to reexamine the connection between stock prices and fundamental factors. It employs recursive structural change tests and cointegration and out-of-sample fit analyses. The results support those obtained with the *Bloomberg* data: short-term stock price fluctuations are related to fundamentals but the relationship between prices and fundamentals is temporally unstable at times and in ways that cannot be fully foreseen.

Beyond shedding new light on the empirical validity of bubble and IKE models, the thesis examines the question of what circumstances cause market participants to pay attention to certain fundamentals over others when forecasting market outcomes. Analyses combining both the *Bloomberg* data and formal econometrics suggest that the frequency with which certain fundamentals merit the attention of market participants is a function of the recent variation of such factors as well as deviations of fundamentals away from estimates of common benchmark levels.

OVERVIEW OF STUDY

The most striking feature of financial markets is the tendency for prices to undergo wide swings away from and back toward estimates of common benchmark levels. The long upswings in equity and housing prices that preceded the recent global financial crisis and the long downswings back toward benchmark levels that followed are but recent examples of this tendency. However, models based on the "Rational Expectations Hypothesis" (REH) have been unable to account for these fluctuations on the basis of market fundamentals such as interest rates and earnings. This failure has led economists to explore two main avenues of research to account for the long-swings nature of equity price movements.

By far the most popular has been to develop REH and behavioral-finance (BF) bubble models, which imply that long swings away from benchmark values occur because over the short-term, market participants persistently look to crowd psychology and technical momentum trading, rather than fundamental factors, in forecasting outcomes and making their trading decisions. The other avenue rests on Imperfect Knowledge Economics (IKE) models (Frydman and Goldberg, 2007, 2011, 2012), which also imply an important role for psychological factors. However, according to this approach, fundamental factors are the main drivers of market participants' forecasts of price and risk in the short-term. Long swings away from and toward benchmark values occur not because participants ignore trends in fundamentals over the short-term, but because these trends are persistent and because they interpret them with inherently imperfect knowledge.

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The key question in this thesis is which class of models – bubble or IKE – provides the better account of long swings in stock prices on the basis of empirical evidence. These models' implications for price swings rest on competing accounts of short-term (daily, monthly, quarterly) movements in prices. As such, my empirical analysis largely focuses on confronting bubble and IKE models' implications for short-term price movements with time series evidence.

The importance of this issue cannot be overstated. Non-bubble REH models underpin the efficient markets hypothesis (EMH), which implies that financial markets are nearly perfect in setting asset prices and allocating society's scarce capital. This conceptual framework was used to justify the massive deregulation that occurred in the U.S. in the two decades prior to the financial crisis. It also led regulators to believe that they did not even have to look for excess in the system, let alone try to dampen this excess as it was building in the run-up to the crisis. This extreme view of markets and the role of the state made the crisis all but inevitable. In the aftermath of the crisis, there has been great urgency to financial reform and calls for a greater role for the state in financial markets.[1] But, which conceptual framework should policy officials and regulators now use to guide them in reforming the financial system?

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[1]For example, the European Systemic Risk Board aims to provide financial market oversight for the European Union. For the United States, the Dodd-Frank Wall Street Reform and Consumer Protection Act, signed into law by President Obama on July 21, 2010, takes prudential steps toward an increased role for the state in financial reform in the aftermath of the financial crisis which began in 2007. In particular, the Financial Stability Oversight Council (FSOC), established under the Dodd-Frank Act, is charged with the management of systemic financial market risk by, for example, directly regulating Over-the-Counter (OTC) derivatives markets and mandating capital and margin requirements and position limits for major market players.

If the asset price swings that we observe in markets result from crowd psychology, speculative fever, and momentum trading, as the bubble models assert, then financial markets often allocate society's scarce capital haphazardly. The bubble view of markets, therefore, rationalizes a strong role for the state to cut off price bubbles as soon as they arise, even if this might require massive intervention. Such intervention would, by design, severely limit financial markets' primary role of allocating society's capital to its most productive uses.

IKE models, on the other hand, provide an intermediate view of markets – they are neither nearly perfect nor driven by irrationalities. Instead, asset price swings in these models are propelled by trends in market fundamentals, such as corporate earnings and interest rates and market participants' imperfect knowledge about how to interpret these trends in forecasting market outcomes. According to this view, price swings are integral to how financial markets allocate capital. However, while markets do a good job, they are not perfect; sometimes they produce price swings that are excessive and that lead to large misallocations of capital.[2] This intermediate view of markets leads to an intermediate view of the state – authorities should set the rules of the game and allow price swings to unfold unfettered, unless they become excessive and move beyond a wide guidance range.[3]

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[2] Asset prices are considered excessive if they have ventured outside a range that reflects what market participants with longer trading horizons would consider consistent with longer-term prospects for projects and companies (Frydman and Goldberg, 2011).

[3] Market participants themselves largely know when prices have far exceeded most estimates of benchmark values. But many care only about short-term profits, and not about the broader social costs of misallocation and the possibility of crisis. Consequently, if trends in fundamentals such as GDP and earnings continue to trend in, say bullish directions, market players would likely continue to bid prices up and further away from benchmark values, even if these movements

Chapter 1 sets the stage for the thesis. I first reinterpret the empirical failure of traditional REH models of stock prices in terms of what I call the "Long Swings Puzzle" – an inability of these models to explain the tendency of equity prices to undergo long swings away from and toward estimates of common benchmark values. The chapter then examines the competing implications of the bubble and IKE classes of models for short-term price movements. Although both approaches imply long swings, their implications for shorter-term price movements differ dramatically. To illuminate these competing implications and to guide analysis in subsequent chapters, I develop a general theoretical framework that encompasses all three classes of models: traditional REH, bubble and IKE. I show that the key distinction between bubble and IKE models is how they model market participants' forecasts of price and risk over the short-term.

The main contributions of the thesis entail new ways to confront bubble and IKE models with empirical evidence. How can we test the predictions of bubble models when psychological and technical trading factors are so difficult to measure, let alone incorporate into formal statistical analysis? Perhaps, this is why bubble models have not, on the whole, been confronted with time-series data.[4] IKE models, on the other hand, imply that the fundamental relationships

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were likely to be excessive (for example, like in the late 1990's). This then provides a role for the state, not because regulators know more than the market, but because they care about the social costs associated with excessive price swings. See Frydman and Goldberg (2011) for more discussion of the externalities associated with financial market speculation.

[4] There are studies that attempt to test for bubbles by looking at market volatility and trading volume, flows of mutual funds and retail investor trading. See Baker and Wurgler (2007) and references therein. These studies, however, typically attempt to match the expansion in stock prices with similar behavior in the microstructure of the market. As such, they provide only an indirect test for stock price bubbles. Shiller (2000a) is an exception in that information is generated through survey expectations of actual market participants.

that drive asset prices change at times and in ways that no one can fully foresee. But, how can we allow for such temporal instability in empirical analysis? In this thesis, I address these problems in several ways.

Chapter 2 sketches the two empirical approaches employed in this thesis. One relies on textual data from *Bloomberg News* and the other on formal econometric analysis. These different approaches can be seen to provide distinct sets of empirical results on the main question of the thesis. However, some of the results of the *Bloomberg* analysis are used to guide the task of translating theoretical models into econometric specifications. Moreover, because the two empirical approaches employed in this study have different limitations, it is useful to examine the extent to which their findings agree.

Chapter 3 presents the textual data compiled from information contained in *Bloomberg News*' daily "market-wrap" (end-of-day) stories for the period from January 1993 through December 2009. The data consist of monthly averages of the frequencies with which a wide range of factors are mentioned in the market wrap stories as a main driver of equity prices. In writing market-wrap stories, *Bloomberg*'s journalists rely on contacts with 100-200 fund managers and other actors directly involved in the markets. These stories provide a window into the decision-making of the professional players whose trading determines prices. My textual data provide a way to measure the relative importance of fundamental, psychological and technical considerations on daily stock price fluctuations without constraining when and in what way these considerations may matter. Chapter 3 also discusses the strengths and limitations of the *Bloomberg* data and

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how they are analyzed. The analysis suggests that IKE models provide the better account of short-term stock price fluctuations. Overwhelmingly, fundamental factors are found to be the primary driver of daily price fluctuations. The analysis also reveals that these factors matter in non-routine ways. Psychological factors, such as confidence, optimism, and fear, are also mentioned quite often, but almost always in connection to a fundamental factor. Pure psychological and technical momentum-related considerations alone, as emphasized by bubble models, are mentioned rather infrequently. There is little evidence in the *Bloomberg* data that would support the bubble view of price fluctuations. To the author's knowledge this is the first study that confronts bubble accounts directly with time series evidence on the importance of psychological factors.

Economists might consider my *Bloomberg* evidence that psychology and technical considerations alone do not drive asset price movements as "too soft" to constitute a formal rejection of the bubble view. The purpose of Chapters 4 and 5 is to provide a more formal statistical analysis of the claim that fundamental factors are the main drivers of short-term stock prices. One of the contributions of these chapters is to use findings from the *Bloomberg* data in carrying out econometric analysis.

One of the problems in conducting econometric analysis is that it is unclear which fundamental factors researchers should include in their econometric model. To address this problem the *Bloomberg* data are used to identify the fundamental factors that merit the most attention from market participants. The factor frequency, for example, with which certain fundamentals

such as earnings, the economy and interest rates were mentioned, was relatively high compared to other fundamentals over the seventeen year period. As a result, the most frequently identified fundamental factors are selected for inclusion in the econometric analysis.

Chapter 4 focuses on the issue of temporal instability in the causal relationship driving stock prices. Most empirical studies of asset pricing models search for fixed-parameter relationships in the data. However, both the *Bloomberg* data and the IKE models imply that this relationship undergoes significant changes at times and in ways that do not follow any mechanical rules. To test for temporal instability, therefore, I use procedures that allow for such non-mechanical change in the causal process. Unlike the analysis with my *Bloomberg* data, I am not restricted to a sample period that covers only the 1990's and 2000's. My sample of monthly data runs from January 1959 through June 2009. But, like the results based on the *Bloomberg* data, I find strong evidence that the fundamental relationship driving monthly stock prices is temporally unstable.

There is no completely objective way to test for temporal instability of causal relationships. Different structural change tests lead to different conclusions about the extent of the temporal instability and the location of breakpoints. This problem leads me to examine whether the locations of breakpoints found on the basis of econometric analysis correspond with those implied based on my *Bloomberg* data. Although the structural change analysis using the *Bloomberg* data is necessarily loose, it suggests a rather high degree

of correspondence between the two analyses. This finding lends support to the results of both analyses.

Chapter 5 uses formal econometric analysis to examine whether fundamentals matter for stock price behavior, as found using the *Bloomberg* data. Beyond the problem of structural change, the issue is complicated by the fact that most conventional macroeconomic and financial time series data are characterized by unit-root processes.[5] The problem is that relationships involving unit-root data can look significant on the basis of classical inference testing, when in fact no relationship really exists. To address the structural change and "spurious regressions" problem, I limit my analysis to examine the relationship in subperiods of statistical parameter constancy, in effect looking for a piece-wise linear relationship. In each regime, I make use of different approaches to test whether there is a fundamental relationship. One approach is the Engle-Granger two-step procedure to test for cointegration, that is, whether there exists an equilibrium relationship between fundamentals and stock prices. Another approach is to extend the Meese and Rogoff (1983) methodology to the stock market by assessing the out-of-sample fit of structural models to that of the simple random-walk. Like with the *Bloomberg* data, I find rather strong evidence of a fundamental relationship operating in the equity market.

Classical econometric analysis assumes that causal relationships are time-invariant. The results from Chapters 3 through 5 suggest, however, that different fundamentals matter in different ways during different time periods.

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[5] A variable that contains at least one unit root is termed non-stationary; the stochastic properties of its mean, variance and covariance are time-variant.

Chapter 6 takes the analysis a step further by asking what considerations lead market participants to focus on certain fundamentals and not others during specific time periods. One hypothesis that I examine is whether individuals pay greater attention to causal factors when they have moved dramatically over recent periods. Another hypothesis posits that the importance market participants place on fundamentals in forecasting market outcomes depends on deviations in the value of these fundamentals from estimates of their own historical benchmark levels. Using my *Bloomberg* data, I find some support for these hypotheses. My findings suggest new ways for incorporating temporal instability into econometric analysis.

CHAPTER I

THE PUZZLING BEHAVIOR OF STOCK PRICES:
COMPETING THEORIES AND IMPLICATIONS

1.1 Introduction

The most striking feature of asset price movements is their tendency to undergo wide swings around estimates of common benchmark levels. The long upswings in equity and housing prices that preceded the recent global financial crisis and the long downswings back toward benchmark levels that precipitated it are but recent examples of this tendency. The inability of models based on the "Rational Expectations Hypothesis" (REH) to account for such fluctuations on the basis of market fundamentals – such as interest rates and overall economic activity – has given rise to two avenues of research.

By far the most popular has been to develop REH and Behavioral Finance (BF) bubble models, which emphasize crowd psychology and technical momentum trading, rather than fundamental factors, as the main drivers of short-term price fluctuations which underpin the long swings behavior. The other avenue develops Imperfect Knowledge Economics (IKE) models, which imply that fundamental factors are the main drivers of asset prices, although psychological considerations also play an important role. The key question in this thesis is to ask which class of models provides the better account of short-term

stock price fluctuations – and thus long swings in prices – when confronted with empirical evidence.

The purpose of this chapter is to set the stage for this research. First, I sketch a canonical REH model of stock prices, which underpins the efficient markets (EM) paradigm. I start with a consumption-based capital asset pricing model (CCAPM) and show how, the traditional present value model, which relates stock prices to dividends and interest rates and has been used widely in the literature, is just a special case. My aim is to illuminate the main implications of this approach for stock price movements.

I turn next to reviewing the empirical record on the EM approach. Much of the empirical research has focused on testing the prediction that in an efficient market, searching for a trading strategy that consistently beats the market on the basis of available information is futile. Put differently, no information set should enable predictability beyond risk-adjusted returns. There is much evidence, however, that stock price movements are characterized by positive serial correlation in the short-run (weekly, monthly and quarterly) and negative serial correlations at longer horizons (3 or more years). The results are widely interpreted as rejections of the canonical model and the EM paradigm.[6] I argue that they are better understood as an inability of the approach to account for the wide swings that often characterize the prices of stocks (and other assets) around benchmark levels.

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[6] Although researchers report correlations over the shorter-term and longer-term, most ignore the problem of temporal instability. This is a theme that runs throughout this thesis. Once we recognize that correlations in returns data are temporally unstable, any correlations that might be found over some past stretch of time do not imply "predictability." See Frydman and Goldberg (2011) for a broader discussion of this issue.

The chapter then examines the competing implications of the alternative bubble and IKE classes of models for price movements. To this end, I develop a general theoretical framework that illuminates these implications and guides analysis in subsequent chapters. While both approaches explain long swings through the market expectation of future prices, they have starkly contrasting implications for shorter-run fluctuations which underpin long swings behavior. The main difference between the bubble and IKE models turns on the relative roles of fundamental, psychological and technical considerations in driving short-term price movements.

The chapter is organized as follows. Section 2 develops a canonical model of stock prices. Section 3 turns to the empirical record on conventional stock price models. The bubble and IKE accounts along with a general theoretical framework are presented in Section 4. Section 5 concludes.

1.2 A Canonical Model of Equity Prices

1.2.1 The Basic Setup

To see the main implications of the EM paradigm I begin with the basic setup of the REH-based CCAPM (Breeden, 1979; Hansen and Singleton, 1983). The model assumes that the typical individual faces the problem at time t of deciding how much of her present and future income and wealth she should consume and save in each and every time period over her lifetime. There are two ways for the individual to save in the model; she can purchase a risk-free asset, called bonds, or a risky asset, called stocks. As such, the individual must also decide how she

should save her resources each period, namely, how much of her wealth she should hold in bonds and stocks. She is assumed to make her consumption-saving and portfolio-allocation decisions for all future time periods at time t. To this end, the individual must forecast her future income, future stock prices, future interest rates, and the future values of all other factors that she deems relevant in forecasting market outcomes.

The canonical CCAPM assumes that individuals are infinitely lived and derive utility solely from consuming goods and services. To portray decision-making, the model assumes that an individual chooses time paths for her consumption and portfolio allocation over her lifetime so as to maximize the expected discounted value of the utility that she will obtain in the present and each future time period, given her present and future expected income. The income stream is assumed to follow a fixed stochastic process and is typically treated exogenously to the setup of the model. The risky asset is portrayed as a claim to future dividend streams. The dividends serve as income and, as such, may be saved or consumed in any time period.

The basic idea of the model is that individuals want to smooth their consumption path relative to their volatile and uncertain income stream. In fact, the canonical models' assumptions about preferences imply that individual's want the same consumption level in every time period and experience disutility from the possibility of unexpected deviations from this flat time path.[7] Because of this

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[7] A flat consumption path follows from the assumption that individuals' subjective discount factor is constant and equal to the risk-free interest rate.

"risk aversion," individuals will hold the risky asset only if they expect a positive return – a premium – over and above the return from holding the risk-free asset.

1.2.2 The Consumption-Based Pricing Equation

More formally, the canonical CCAPM assumes that individual, i, maximizes the discounted stream of utility from individual consumption in the present and all future time periods:

$$E_t\left[\sum_{j=0}^{\infty} \beta^j U\left(C_{t+j}^i\right) | I_t\right],$$ (1)

where β is the subjective discount factor and measures an individuals' level of impatience ($\beta < 1$), C_{t+j}^i denotes individual consumption at time $t+j$, $U(\cdot)$ is a time-separable period utility function, which is assumed to be time-invariant and to obey U'(C)>0 and U''(C)<0, and E_t is the expectation operator conditional on information available at time t, I_t. This maximization is subject to the following budget constraint:

$$C_t^i + A_t^i P_t + B_t^i = Y_t^i + A_{t-1}^i \left[\frac{(P_t + D_t)}{P_{t-1}}\right] + B_{t-1}^i\left(1 + r_t^f\right)$$ (2)

where, A_t^i denotes the number of units of stock, P_t is the price of stock at time t, B_t^i is the value of risk-free bonds held at time t which promises to pay with certainty the nominal return r_t^f, Y_t^i is an individual's income and D_t denotes the dividend paid at time t. The right-hand side of the equality represents an individual's wealth at the beginning of period t. Choosing consumption, C_t^i, and

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an allocation, A_t^i, to the risky assets yields the following first-order condition or Euler equation for individual i from this optimizing problem:[8]

$$P_t U'^i(C_t^i) = E_t^i[\beta U'^i(C_{t+1}^i)(P_{t+1} + D_{t+1})|I_t^i] \qquad (3)$$

Equation (3) says that the individual chooses consumption in every period so that the marginal disutility from reducing her consumption by one additional unit at time t and buying a little more of the risky asset equals the expected discounted marginal utility gain from consuming the proceeds of the asset's payoff in period *t+1*.

Asset market models typically determine price as the value that balances the total individual demands with the total of individual supplies of an asset. In general, individuals differ in terms of their preferences and forecasting strategies, which makes it difficult, and in many cases impossible, to express the aggregates of demands and supplies as well defined relations of price and other variables. The vast majority of economic models, including the canonical CCAPM model, deal with this problem by relying on the representative agent assumption, that is, by assuming it away.[9] With this assumption, equation (3) can be expressed as a relationship between prices and aggregate consumption:

$$P_t U'(C_t) = E_t[\beta U'(C_{t+1})(P_{t+1} + D_{t+1})|I_t] \qquad (4)$$

To obtain an expression for the stock price, we divide both sides of (4) by $U'(C_t)$, giving the basic consumption-based pricing equation:

$$P_t = E_t[\delta_t(P_{t+1} + \dot{D}_{t+1})|I_t] \qquad (5)$$

---

[8] Equation (3) follows from the two first-order conditions to the maximization problem.

[9] Assuming a representative agent implies all individuals within the economy are identical; there is a "typical" consumer whose preferences and forecasting behavior are equivalent to the average of those on the aggregate level.

At every point in time, the stock price today equals the expected discounted value of tomorrow's payoff, where $\delta_t = \beta \frac{u'(C_{t+1})}{u'(C_t)}$ is called the stochastic discount factor (SDF). The SDF expresses tomorrow's dollars in value today. In the current framework, the SDF equals the ratio of marginal rates of substitution between consumption at time *t* and consumption at time *t+1*, or the intertemporal marginal rate of substitution (IMRS).

1.2.3 Assuming Away Change in Forecasting

Equation (5) may also be written as,

$$P_t = E_t(\delta_{t+1} X_{t+1} | I_t) \tag{6}$$

where $X_{t+1} = P_{t+1} + D_{t+1}$. Applying the definition of covariance and iterating the equation forward one period and using the result to express the future price in terms of D_{t+1}, D_{t+2} and P_{t+2} yields:[10]

$$P_t = E_t(\delta_{t+1})E_t(D_{t+1}) + E_t(\delta_{t+1})E_t[E_{t+1}(\delta_{t+2})E_{t+1}(P_{t+2} + D_{t+2})]$$

$$+E_t(\delta_{t+1})cov_{t+1}(\delta_{t+2}, X_{t+2}) + cov_t(\delta_{t+1}, X_{t+1}) \tag{7}$$

This expression shows that to determine price in the canonical model, economists must specify how the market forecasts at time *t* how it will forecast at time *t+1*, that is, it must represent how individuals think they might change the way they will think in the future. In general, we would expect that individuals do in fact revise their forecasting strategies over time, at least intermittently. How to model such revisions presents a formidable challenge to macroeconomics and finance theory.

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[10] The equation for covariance is, $cov(M, X) = E(MX) - E(M)E(X)$.

Like the aggregation problem, however, the vast majority of economists

assume away the problem. By relying on REH, individuals are assumed to never

change the way they forecast market outcomes In this case, the "law of iterated

expectations" (LIE) applies.[11] The canonical model also assumes away any

explosive behavior by assuming that the expected discounted value of the stock

price goes to zero as t approaches infinity,[12]

$$\lim_{\iota \to \infty} E_t\left[\left(\delta^{t+\iota}\right)P_{t+\iota}\right] = 0 \tag{8}$$

Imposing LIE and the transversality condition in (8), along with forward

iteration of (7), yields an expression for the stock price in terms of the stream of

dividends into the future and the covariance of dividends with the SDF.[13]

$$P_t = P_t^* = E_t\left[\sum_{\iota=1}^{\infty} \delta^{\iota} D_{t+\iota} \mid I_t\right] + \sum_{\iota=0}^{\infty} \delta^{\iota} cov_{t+\iota}(\delta_{t+1+\iota}, D_{t+1+\iota}) \tag{9}$$

where P_t^* is the risk-adjusted fundamental or intrinsic value of the stock – the

expected present value of the future stream of dividends plus the covariance of

dividends with the SDF.[14] The second term on the right-hand side of (9) is the

market risk premium. If the stock pays off well when marginal utility is low

(consumption is high), which would be the case if $cov_t(\delta_{t+\iota}, D_{t+\iota}) < 0$, the stock

would have to sell at a lower price to induce individuals to hold it. Only then

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[11] The law of iterated expectations states that $E_t[E_{t+1}[Z]] = E_t[Z]$

[12] This assumption implies that expectations of future price increases for individuals with infinite trading horizons will be bounded Imposing the terminal condition assures that individuals will not always expect the price of stock next period to be higher than it is today The REH bubble models relax this assumption See Section 4

[13] The solution for price is, $P_t = \sum_{\iota=1}^{\infty}\left(\prod_1^{\iota} E_t(\delta_{t+\iota})\right)E_t(D_{t+\iota}) +$ $\sum_{\iota=0}^{\infty}\left(\prod_1^{\iota} E_t(\delta_{t+\iota})\right)cov_{t+\iota}(\delta_{t+1+\iota}, X_{t+1+\iota})$ In general, δ is time varying, but we assume that it is governed by a stationary distribution, so that, $E_t(\delta_{t+\iota}) = \bar{\delta}$ We also assume that $\delta < 1$ and sufficiently so that the product series converges, leaving equation (9)

[14] Ownership of an equity share is a claim to the future income and assets of a firm The intrinsic value of an asset is merely the present discounted value of this cash flow

would individuals expect a higher return to compensate them for holding stocks.[15]

To see this, note that a lower P_t implies a higher return, r_{t+1}, from holding stocks

one period:

$$r_{t+1} = \frac{P_{t+1}+D_{t+1}}{P_t} - 1 \tag{10}$$

1.2.4 The Traditional Present Value Model

Many studies, including Fama (1965) and Samuelson (1965), ignore the

implications of risk by assuming risk-neutrality, i.e. individuals care only about the

expected return on assets; they do not worry about random unexpected changes

in their income and consumption and so do not care about the volatility of these

variables. To portray risk-neutrality in this setup, economists make use of a linear

utility function, which implies that δ_t is constant at every point in time. As such,

$cov_t(\delta_{t+1}, D_{t+1}) = 0$, and we have,

$$P_t = E_t \left[\frac{P_{t+1}+D_{t+1}}{1+r^f} | I_t \right] \tag{11}$$

The stock price at each time t depends on the market's forecast of the one-

period-ahead price and dividend. According to equation (11), the expected return

on stocks is constant and equal to the return on bonds, $E_t[r_{t+1}] = r^f$, since

$E_t \left[\frac{P_{t+1}+D_{t+1}}{1+r^f} | I_t \right] - 1 = r^f$.

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[15] Conversely, if the stock's payoff covaries positively with the SDF, the stock pays off well when the marginal utility is high (consumption is low). In this case stocks are not risky, but provide insurance against bad states of nature. In this case, stocks will sell at a discount to bonds and so fetch a higher price in the market.

Equation (11) is solved for a reduced form of the stock price by repeated forward iteration and by applying LIE and the terminal condition in (8). This yields the following expression for the stock price:

$$P_t = P^* = E_t\left[\sum_{i=1}^{\infty} \delta^i D_{t+i} \,|I_t\right] \tag{12}$$

where $\delta = \frac{1}{1+r^f}$. With REH, the fundamental or intrinsic value of the stock depends on the expected future stream of dividends.

In order to relate this intrinsic value and thus the stock price to current information and so derive testable implications from the model, we need to specify a process for dividends. In general, this process changes in non-routine ways over time and could depend on many factors such as interest rates, GDP growth rates, and technological advances. But, the vast majority of researchers assume away all non-routine change. Moreover, it is typical in the literature to assume a univariate process for dividends, such as,

$$D_t = (1+g)D_{t-1} + \varepsilon_t \tag{13}$$

where g is the constant dividend growth rate, and ε_t is a stochastic error term that is uncorrelated with past information and averages to zero over time. The conditional probability distribution in equation (13) for dividends is assumed to apply at every point in time, past, present and future.

In portraying forecasting behavior, REH assumes that individuals know the true dividend process in (13) and use it to forecast future dividends. Consequently, imposing REH in the model gives rise to a fixed stochastic

process for the stock price. To see this, we repeatedly iterate (13) forward and express all future dividends in terms of D_t:[16]

$$E_t[D_{t+i}] = (1 + g)E_t[D_{t+i-1}] = (1 + g)^i D_t \qquad (14)$$

Plugging (14) into (12) gives the traditional and widely used Gordon growth model for stock prices (Gordon, 1962):

$$P_t = \frac{E_t[D_{t+1}]}{r^f - g} = \frac{(1+g)D_t}{r^f - g} \qquad (15)$$

where $g < r^f$.[17]

1.2.5 Key Implications of the Model

We see from (15) that the canonical model implies not only that the intrinsic value of stocks depends in a fixed way on the current dividend, its growth rate, and the risk-free rate, but that the price-dividend ratio is constant.

This REH theory underpins what many refer to as the Efficient Markets Hypothesis (EMH), that "prices always 'fully reflect' available information" (Fama, 1970, p. 383). By implying that stock prices are always equal to their intrinsic values, EMH implies that markets set asset prices nearly perfectly. This implication, in turn, implies that available information cannot be used to predict, on average, stock returns.

To see this second implication, recall that individuals are assumed to know exactly, up to a stochastic error term, the true behavior governing dividends: the market's assessment of the stock's intrinsic value is assumed to

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[16] Having assumed a time invariant dividend process, REH again allows us to make use of LIE.

[17] The inequality $g < r^f$ is necessary for a well-specified expression for price in the Gordon growth model. See Appendix for details.

be correct on average. Consequently, the actual stock price change will differ from the intrinsic value only as a result of new information – arising in the form of "news" captured by a random error term – that influences the dividend process. As news about dividends becomes available and individuals learn that the stock's intrinsic value has changed, they immediately bid prices to this new value. As such, the model implies that it is impossible to predict returns using available information. This is the martingale property showcased by Samuelson (1965).

In this way, EMH implies that markets set prices nearly perfectly and that it is impossible to beat the market on average. Much of the empirical work on EMH focuses on the implication of the non-predictability of returns.

1.3 The Empirical Record of the Canonical Model

Financial economists have undertaken many empirical studies examining whether, in fact, returns in asset markets are unpredictable with available information as implied by REH theory and EMH. Researchers have looked for significant autocorrelations over the short-term and longer-term, as well as whether returns are correlated with a broader information set, including interest rates, inflation rates and price-to-earnings (P/E) ratios. The early studies of the 1970's mostly reported no evidence of predictability and so gave support to EMH. However, beginning in the 1980's, researchers began reporting results that were inconsistent with this hypothesis.

1.3.1 Reports of Short-Term Autocorrelation

Many studies now report that over the short-term, (weekly, monthly or quarterly horizons), stock returns are positively serially correlated (Cutler *et al.*, 1991; Jegadeesh and Titman, 1993; Chan *et al.*, 1996; and Lo and MacKinlay, 1999). A particularly important study is Lo and MacKinlay (1999), which finds positive and large weekly autocorrelations of 30% for the equal-weighted Center for Research in Security Prices (CRSP) returns index from 1962 through 1985.

This finding has also been referred to as "momentum" by Jegadeesh and Titman (1993). In their study, stocks are grouped into deciles based on the highest and lowest cross-section of monthly returns from 1963 through 1989. The authors report that the stocks with the highest returns over the previous six months outperform those with the lowest past returns over the ensuing six months by an average of 10% over the sample period.

1.3.2 Reports of Longer-Run Negative Autocorrelation

There is also considerable evidence that stock returns are negatively autocorrelated over longer horizons of three years or longer (De Bondt and Thaler, 1985; Poterba and Summers, 1988; Fama and French, 1988; Campbell and Shiller, 1988, 2001). The influential study of De Bondt and Thaler (1985) examines the long-horizon returns of two portfolios of stocks: a "winner" portfolio of the 35 best performing stocks over the preceding three year period and a "loser" portfolio of the 35 worst performing stocks. In a sample that runs from

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1926 through 1982, De Bondt and Thaler report that, over the subsequent three years, the "loser" portfolio, on average, outperforms the "winner" portfolio by 8%.

It is unclear whether this evidence really represents a rejection of EMH. The problem is that studies do not allow for temporal instability. Correlations that are found in past stretches of data are unstable, so one cannot merely rely on past correlations to predict future returns.[18] But, the IKE model that I sketch below, suggests that the evidence on "return predictability" is reflective of the tendency for asset prices to undergo wide swings around estimates of commonly-used benchmark values.

1.3.3 Long Swings Behavior

The long swings behavior of stock prices is illustrated in Figures 1.1 and 1.2, which plot the Standard and Poor's 500 Composite Index Price relative to a 10-year trailing average of earnings and dividends, respectively, and examples of benchmark levels.[19] The figures show that stock prices tend to move from one month to the next in one direction for long periods time, which would give rise to positive serial correlations in monthly returns. The figures also show that long swings away from benchmark values are ultimately bounded; eventually long

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[18] The evidence that correlations in asset market data are unstable is overwhelming. See Frydman and Goldberg (2011) and references therein.

[19] The data for Figure 1.1 are taken from Shiller (2000b) which are updated on his website. Figure 1.2 is taken directly from Campbell and Shiller (2001, Figure 4). The benchmark levels used in the figures are only examples. In general, there are many ways to measure benchmark values, including time-varying representations. By construction, the P/E and P/D ratios will swing around their long-run averages. But, it is important to note that the swings occur because of swings in P away from and towards benchmark values based on earnings and dividends.

upswings are followed by sustained counter-movements. Such behavior would give rise to negative serial correlations in returns at longer horizons.

Indeed, researchers have produced much evidence that while P/E and P/D ratios can undergo long swings, they are mean reverting; the market eventually self-corrects. For example, using stock returns for the New York Stock Exchange (NYSE) over the period 1941 through 1986, Fama and French (1988) find that the price-dividend ratio explains 27% of the variation in cumulative stock returns at four year horizons. Poterba and Summers (1988) find similar evidence of mean reversion in stock returns in the form of significant negative autocorrelations at eight year horizons. Campbell and Shiller (1987) use cointegration analysis and report evidence that stock prices and dividends share a longer-run relation.

The evidence suggests that when prices are high relative to benchmark levels based on long-run averages of P/E or P/D ratios, subsequent returns over the next five to ten years are likely to be below average. As John Cochrane stated in a recent interview, "when stock prices are high relative to earnings – that seems to signal a period of low returns...we all agree on that fact" (Cassidy, 2010, p. 1).

1.3.4 Explaining Long Swings with the Canonical Model?

The empirical evidence on the tendency for stock prices to undergo wide but bounded swings relative to underlying earnings or dividends, conflicts with the canonical models' prediction that P/E and P/D ratios should be constant. This

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has led researchers to modify the canonical model so that it can account for this behavior. According to this model, the stock price is always equal to its intrinsic value. Consequently, to account for swings, researchers have looked for reasons why this intrinsic value would undergo swings. EMH proponents have appealed to swings in the market's risk premium (Fama and French, 1989; Campbell and Cochrane, 1999; Cochrane, 2011).

With a risk premium, the intrinsic value for stock equals the summation of both terms on the right-hand side of equation (9). Consequently, this intrinsic value rises if the market's risk premium falls because individuals would become more willing to purchase claims to uncertain dividend streams. Conversely, the stock's intrinsic value would fall if the market's risk premium rises.[20] Consequently, to account for swings in stock prices, the canonical model would need to explain why there are long-lasting periods in which risk-premiums fall and rise. However, ever since Mehra and Prescott (1985), economists have known that traditional REH-based risk premium models are grossly inconsistent with time-series data on returns in stock and other asset markets.[21]

Researchers have attempted to account for a time-varying risk premium by allowing for habit-persistence (Abel, 1999; Campbell and Cochrane, 1999). In these accounts, an individuals' appetite for risk moves inversely with the state of the economy. During prosperous times, individuals are more willing to take on risk, which drives up intrinsic values. Conversely, depressed times are

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[20] Note, we are defining the risk premium as a negative value. For a risk premium to exist, the asset's payoff would have to covary negatively with the SDF.

[21] For a survey of the large literature on the equity premium puzzle see Goyal and Welch (2008) and references therein.

associated with an unwillingness to bear risk, thereby exerting downward pressure on intrinsic values. There is much evidence, however, that allowing for habit-persistence does not save the CCAPM (Duffee, 2005).

Despite this failure, economists continue to appeal to this model to explain swings in the market risk premium. For example, Fama and French (1989) argue that the large upswing that occurred in the 1990's, arose because of a booming economy. As pointed out by Frydman and Goldberg (2011), however, this appeal to a time-varying risk premium to explain stock price swings is inconsistent with empirical evidence. The long upswing in stock prices that began in the early 1980's persisted unabated through the economic recession of 1991, which should have been associated with rising risk premia and a downturn in the market if Fama and French's account were correct. Moreover, stocks started falling already in early 2000 even though the recession in the economy did not materialize until a year later.

Cochrane (2008, 2011) admits that economists have not yet developed an REH-based model of the risk premium that can account for asset price swings. But, researchers remain steadfast in their pursuit. As John Cochrane stated in a recent interview, "That's the challenge. That's what we all work on" (Cochrane in Cassidy, 2010, p. 3).

The empirical failures of the REH theory to explain swings in stock prices on the basis of fundamental considerations has led economists to develop two competing approaches: bubble models and IKE models.

1.4 Competing Views: A Composite Theoretical Framework

The purpose of this section is twofold. One is to examine the key similarities and differences between how the canonical, bubble and IKE models attempt to account for price swings in equity markets. The other is to uncover the competing implications of the bubble and IKE models of price swings. To these ends, I show that all three classes of models can be seen as special cases of the following composite model:

$$P_t = P_t^{BM} + c_t\left(\hat{P}_{t|t+1} - \hat{P}_{t|t+1}^{BM}\right) \tag{16}$$

where a "$\hat{}$" denotes the market's point forecast of the future stock price made at time t for time $t+1$, P_t^{BM} is the stock's benchmark value, c_t is a parameter and P_t, is as defined before.

1.4.1 The Canonical Model

To see how the canonical model can be expressed as in (16), note that equation (5) can be written as follows:

$$P_t = a_t + b_t(1 + g)D_t + c_t\hat{P}_{t|t+1} \tag{17}$$

where $a_t = 0$, $b_t = c_t = \delta$, and we have used that $E_t D_{t+1} = (1 + g)D_t$.[22] By adding and subtracting $c_t\hat{P}_{t|t+1}^*$ in (17) gives us:

$$P_t = a_t + b_t(1 + g)D_t + c_t\hat{P}_{t|t+1}^* + c_t\left(\hat{P}_{t|t+1} - \hat{P}_{t|t+1}^*\right) \tag{18}$$

Equation (16) immediately follows because[23]:

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[22] Assuming risk neutrality implies a constant δ equal to $\frac{1}{1+r^f}$.

$$P_t^* = a_t + b_t(1 + g)D_t + c_t\hat{P}_{t|t+1}^* \tag{19}$$

As such, equation (16) can be written as:

$$P_t = P_t^* + c_t\left(\hat{P}_{t|t+1} - \hat{P}_{t|t+1}^*\right) \tag{20}$$

where $P_t^* = P_t^{BM}$. Equation (20) suggests that the market's expectation $\hat{P}_{t|t+1}$ is the key variable behind swings in the stock price away from and toward the benchmark P_t^*.

However, by design, REH implies that expectations are endogenous – an output rather than an input - to the model. Consequently, the market's forecast of price next period is merely the expected intrinsic value next period: $\hat{P}_{t|t+1} = \hat{P}_{t|t+1}^*$. We already know that equation (20) collapses to $P_t = P_t^*$.

Without the freedom to explore alternative assumptions about price expectations in the canonical model, researchers must rely on alternative specifications of preferences or in another non-expectational component to generate swings in the stock's intrinsic value, P_t^*. As we have seen, Fama and French (1989) is one example of this research avenue.

By sharp contrast, the bubble and IKE accounts model market participants' price forecasts as an autonomous component of the model. These approaches account for long swings in stock prices with competing portrayals of movements in the market's expectation, $\hat{P}_{t|t+1}$ over the shorter-term.

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[23] REH assumes $\hat{P}_{t|t+1}^* = E_t[P_t|I_t] = \delta E_t[D_{t+1}] = \delta(1 + g)D_t$.

1.4.2 Bubble Models: Mechanical Swings in Expectations

Although researchers have developed many different bubble models, these models share a common narrative.[24] The basic idea behind them is that for various reasons, market participants begin to increasingly ignore fundamental considerations in making their short-run trading decisions. They instead base them on non-fundamental factors such as crowd psychology, speculative fever, and technical momentum trading. This short-term speculation, in turn, leads them to push prices increasingly away from levels based on fundamental factors. As Peter Garber (2000, p. 4) put it, bubbles are the "...part of asset price movement that is unexplainable based on what we call fundamentals." Eventually, however, bubbles burst: there are reasons in the models that lead market participants to once again focus on fundamental considerations in their trading decisions, which immediately bring prices back towards levels consistent with fundamentals.

The idea that market participants sometimes ignore fundamental considerations in their trading decisions has a long history in finance and economics. Famous upswings in market prices that are commonly thought to be bubbles include the Dutch Tulip Mania (1634-36), the Mississippi Bubble (1719-20), the English South Sea Bubble (1720) and the U.S. stock market expansion of the roaring 1920's.[25] More recent accounts that are thought to be good examples of bubbles include the increase in Japanese real estate prices of the

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[24] For surveys of the various bubble approaches, see Camerer (1989) and Brunnermeier (2008).

[25] Charles Mackay's *Extraordinary Popular Delusions and the Madness of Crowds* was one of the first comprehensive accounts of the psychological state of financial markets and its implications for asset price behavior (Mackay, 1932). For an historical account of price level bubbles and financial crises see the enormously popular *Manias, Panics, and Crashes* by Kindleberger (2000).

1990's, the dramatic upswing in U.S. equity prices associated with the

technology boom of the late 1990's and the rise of U.S. housing prices from

2003-2006.

Whether the long upswings in U.S. stock prices in the 1920's and 1990's

are best thought of as bubbles – movements that are unrelated to fundamental

considerations – or as a result of imperfect knowledge and trends in fundamental

factors is the topic of this dissertation. The evidence reported in this thesis

provides very little support for the bubble view in stock markets. This conclusion

is suggestive that the dramatic upswings that have occurred in other markets

may also be better understood not as bubbles but as related to fundamentals.

Unlike the canonical model, the bubble models generate swings in asset

prices because of swings in market participants' price forecasts away from

values based on fundamentals. The reasons for why market participants

abandon fundamental considerations in their trading decisions differ across

models. Most models emphasize psychological and momentum-related factors

as driving short-term stock price movements. According to a leading behavioral

economist, "...*mass psychology* may well be the dominant cause for movements

in the price of the aggregate stock market" (Shiller, 1984, p. 459, emphasis

added).

1.4.3 REH Bubble Models

The REH setup that underpins the canonical model admits a more general

solution than in equation (12), where $P_t = P_t^*$. In general, the solution to the

stochastic difference equation in (11) includes an explosive price term, which the canonical model assumed was zero by imposing the terminal condition in (8), in addition to the particular solution, P_t^*. This additional term allows the market's expectation of future prices to differ from that of the expected future intrinsic value of the stock: $\hat{P}_{t|t+1} \neq \hat{P}_{t|t+1}^*$.

REH bubble models can be seen as a special case of (16). In these models, the markets' expectation follows:

$$\hat{P}_{t|t+1} = \hat{P}_{t|t+1}^* + E_t B_{t+1} \qquad (21)$$

where B_t is the "bubble" term. Plugging (21) into (20), we have:

$$P_t = P_t^* + c_t\left(\hat{P}_{t|t+1}^* + E_t B_{t+1} - \hat{P}_{t|t+1}^*\right) \qquad (22)$$

It immediately follows that:

$$P_t = P_t^* + c_t E_t[B_{t+1}|I_t] \qquad (23)$$

In the context of equation (11), the bubble term is formally expressed as,

$$E_t[B_{t+1}|I_t] = (1 + r^f)B_t \qquad (24)$$

implying that $c_t = \delta$ in equation (22). In order to explain the wide swings in stock prices, REH bubbles must further specify the dynamics governing the behavior of the bubble term in (24).

In order to explain price swings, the seminal study of Blanchard and Watson (1982) assumes that the bubble does not exist in every period. At times, the bubble term equals zero ($B_t = 0$) and market participants' expectations are determined by fundamentals only. In this case, the stock price is equal to its intrinsic value, P_t^*. At other times, the bubble term is different from zero ($B_t \neq 0$) because individuals increasingly pay attention to non-fundamental factors in the

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short-run, such as crowd psychology and speculative fever. With REH, everyone believes that the stock price will deviate from fundamentals at an increasing rate. This implies that beliefs of higher future prices are self-fulfilling. This justification of expectations of higher future prices perpetuates the increase in stock prices.

To see this, the authors write down a framework governing the bubble term,

$$B_{t+1} = \begin{cases} \left(\frac{1+r^f}{\pi}\right) B_t + \varepsilon_{t+1} & with\ probability\ \pi \\ \varepsilon_{t+1} & with\ probability\ 1 - \pi \end{cases} \qquad (25)$$

where $E_t[\varepsilon_{t+1}|I_t] = 0$. At any period in time, the price bubble is assumed to be zero with probability $1 - \pi$. If not, the bubble exists with probability π and is assumed to grow at a rate $\left(\frac{1+r^f}{\pi}\right)$, which is greater than r^f in order to compensate individuals for the probability of the bubble bursting.

The main implication of the REH bubble model is that it generates swings away from benchmark levels because all individuals, impacted by purely psychological and momentum-related considerations, increasingly ignore fundamental factors in forming short-term price expectations. With REH, this implies that expectations are self-fulfilling. If this model were correct, we would expect to see stock prices rise independently of trends in fundamental considerations, such as earnings. Even if earnings fell, we could get an upswing in prices away from P_t^*.

However, it is unclear what causes REH bubbles to begin and end, i.e. what triggers market participants to collectively ignore and then reconsider fundamentals in forming price forecasts. Moreover, there are numerous

theoretical implications (Diba and Grossman, 1988; Santos and Woodford, 1997) and empirical shortcomings (Frydman and Goldberg, 2011) that compromise this view.

1.4.4 Behavioral Bubble Models

Behavioral bubble models attempt to portray how market participants actually behave.[26] Drawing on insights from psychology and sociology, behavioral economists have found that individuals have difficulty assessing probabilities of market outcomes when faced with uncertainty. This has led economists to develop models involving the interaction of "intelligent investors" – who are portrayed with REH or with an optimal learning rule based on Bayes' Law – and unintelligent or "noise" traders who are, "...variously subject to *animal spirits*, fads and fashions, *overconfidence* and related psychological biases that might lead to *momentum trading*, *trend chasing*, and the like" (Abreu and Brunnermeier, 2003, p.173, emphasis added). Models of this type include De Long *et al.* (1990a,b) and Abreu and Brunnermeier (2003).

Asset price swings in behavioral bubble models arise because unintelligent market participants' trading decisions drive short-term stock price movements persistently away from levels consistent with fundamental considerations by buying when prices are rising and selling when they are

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[26] For a survey of behavioral finance, see Barberis and Thaler (2002).

falling.[27] As such, their expectations of future prices are determined by past price changes.

In the context of equation (20), swings in the market's expectation $\hat{P}_{t|t+1}$ away from $\hat{P}^*_{t|t+1}$ arise because of the relative weights attached to it by intelligent and unintelligent traders:

$$\hat{P}_{t|t+1} = \alpha \hat{P}_{t|t+1} + (1 - \alpha)\hat{P}_{t|t+1} \tag{26}$$

where α is the proportion of smart traders populating the market, making $(1 - \alpha)$ the proportion of unintelligent traders . Plugging (26) into (20) gives:

$$P_t = P^*_t + c_t\big(\alpha \hat{P}_{t|t+1} + (1 - \alpha)\hat{P}_{t|t+1} - \hat{P}^*_{t|t+1}\big) \tag{27}$$

Because $\alpha \hat{P}_{t|t+1} = \hat{P}^*_{t|t+1}$, (27) may be written as,

$$P_t = P^*_t + c_t(1 - \alpha)\hat{P}_{t|t+1} \tag{28}$$

To see how this behavior is portrayed, consider the model of positive feedback and momentum trading of De Long *et al.* (1990b). The model assumes that the unintelligent participants are feedback traders, whose demand for stock depends on past price changes. The smart traders' forecasting behavior is portrayed with REH and as such, their demands are inversely related to the departure of prices from fundamental values.[28]

Feedback traders' expectations, and thus their demand for stock, are assumed to follow:

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[27] In Abreu and Brunnermeier (2003), the so-called rational traders can also push prices away from true intrinsic values if their open positions relative to those by the irrational traders are small enough.

[28] The model also assumes passive traders, who also bet on reversals in prices. Unlike smart traders, passive traders do not, on average, know the stock's intrinsic value ahead of time; they must wait for public information to reveal it to them in every period.

$$\hat{P}_{t|t+1} = D_t^f = \beta(\Delta P_t) \tag{29}$$

where β is the feedback coefficient measuring the responsiveness to past price changes ($\beta > 0$) and Δ is the first difference operator. Equation (29) implies that in forming expectations, feedback traders ignore fundamentals by merely extrapolating past price changes. As a result, stock prices depart from P_t^* for some indeterminate amount of time. Like most bubble models, what causes deviations from fundamentals to begin and end is not clear. Price reversals occur in this model because in the final period of trading, smart traders, "pin the stock price down to its fundamental value" (De Long *et al.*, 1990b, p. 384).

Like the REH bubble models, the behavioral feedback model generates temporary swings in stock prices because individuals' ignore fundamental considerations. Instead of crowd psychology and speculative fever, short-term stock price movements, and thus price swings, arise from technical trading and extrapolation of price trends, which are considered more prevalent in financial markets than crowd psychology. However, trading strategies relying on technical trading typically only consider horizons as short as minutes to hours, making it difficult to explain long swings in prices under this account (Frydman and Goldberg, 2011).[29]

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[29] The extent to which the extrapolation of past price trends occurs in financial markets remains an open question. Schulmeister (2003, 2006) notes that technical trading rules focus on the timing of investment decisions given past price trends and conjectures that the implementation of such strategies are only viable over the very short term, i.e. minutes, hours, or days.

1.4.5 IKE Models: Non-Mechanical Swings in Expectations

Like the bubble models sketched in the preceding section, Frydman and Goldberg's (2007, 2012) IKE model of asset prices and risk explains price swings as the result of swings in the market's expectation of the future price, $\hat{P}_{t|t+1}$.[30] However, unlike the bubble approach, short-term price movements and swings in $\hat{P}_{t|t+1}$ occur because of trends in fundamental considerations and imperfect knowledge about how to interpret these trends in forecasting market outcomes.

IKE models express equilibrium in asset markets by equating the market's expected return with the market premium.[31] This is an equilibrium condition that equates the total buying and selling of bulls and bears in the marketplace (see Appendix for derivation). More formally,

$$\hat{r}_{t|t+1} = \widehat{pr}_{t|t+1} \tag{30}$$

The left-hand side of equation (30) is the market's expected return. Recall that the *ex ante* return on holding stock, in logarithmic form, is:

$$\hat{r}_{t|t+1} = \hat{P}_{t|t+1} - P_t - r_t^f \tag{31}$$

The right-hand side of equation (30) is the market premium required by individuals to compensate them for the risk associated with holding an open position in stock. IKE models express this term as:

$$\widehat{pr}_{t|t+1} = \widehat{up}_{t|t+1} + \lambda \frac{S_t}{W_t} \tag{32}$$

where $\widehat{up}_{t|t+1}$ is the uncertainty premium and S_t and W_t are supplies of stock and market wealth, respectively. The uncertainty premium required to take an open

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[30] The IKE model of asset price swings and risk is based on an alternative specification of preferences and decision-making under uncertainty dubbed Endogenous Prospect Theory (EPT).

[31] The market premium is based on Endogenous Prospect Theory (see appendix).

position is equal the potential losses from the speculative decisions of bulls and bears who hold long (L) and short (S) positions, respectively:

$$\widehat{up}_{t|t+1} = \frac{1}{2}\left(\hat{l}^L_{t|t+1} + \hat{l}^S_{t|t+1}\right) = \hat{l}_{t|t+1} \tag{33}$$

To model the expected potential loss from speculating, IKE models relate it to the deviation of prices from estimates of common benchmark levels:

$$\hat{l}_{t|t+1} = \sigma_t(P_t - P_t^{BM}) \tag{34}$$

where P_t^{BM} represents an estimate of a common benchmark level and $\sigma_t > 0$. IKE recognizes that stock and other asset prices move away from benchmark levels for years at a time. However, this departure is ultimately bounded; price swings undergo reversals back towards, and often shoot through, benchmark levels, which themselves are varying. In the IKE model, as the assessment of the price-gap increases so does the potential loss from holding a speculative position. As a result, the market premium also increases.

Assuming that risk-free rates and the ratio of supplies to wealth are relatively small and constant, we can plug (31) and (34) into (30) giving us:

$$P_t = \hat{P}_{t|t+1} - \sigma_t(P_t - P_t^{BM}) \tag{35}$$

Rearranging and adding and subtracting P_t^{BM} from the right-hand side yields:

$$P_t = P_t^{BM} + \left(\frac{1}{1+\sigma_t}\right)\left(\hat{P}_{t|t+1} - P_t^{BM}\right) \tag{36}$$

It is immediately evident that (36) is a special case of (16), where $c_t = \frac{1}{1+\sigma_t}$.

Like the bubble models, swings in P_t away from the benchmark arise because of swings in the market expectation, $\hat{P}_{t|t+1}$. Price swings end when

swings in $\hat{P}_{t|t+1}$ end. IKE models, however, have different explanations of swings

away from and towards benchmark levels and why they are ultimately bounded.

Unlike the canonical and bubble models, the IKE model recognizes that no

one, including economists, knows what the true fundamental value for stocks is.

However, Keynes (1936, p. 201) understood that market participants use

historical benchmark values as a guide to unknown intrinsic values and that

individuals' account for these values when forecasting. In assessing the decision

faced by market participants of whether to hold wealth in the form of cash versus

interest-bearing bonds, Keynes (1936, p. 201) argues,

> [the demand for cash] will not have a definitive quantitative relation
> to a given rate of interest r, what matters is not the *absolute* level of
> r but the degree of its divergence from what is considered a fairly
> *safe* level of r, having regard to those calculations of probability
> which are being relied on.

In the IKE model, the deviation of prices from benchmark levels (the gap)

helps individuals forecast potential losses. This implies that the market premium

helps to dampen swings: as $\hat{P}_{t|t+1}$ moves away the market premium rises and so

a smaller rise in P_t is required to maintain market equilibrium. This stands in

sharp contrast to the implications for risk in the canonical model; instead of

driving swings in asset prices, risk in IKE models bounds swings in asset prices.

To see how the IKE model portrays forecasting and swings in $\hat{P}_{t|t+1}$,

consider a more formal account of Frydman and Goldberg's IKE model. The

forecast of next period's stock price for individual i is:

$$\hat{P}^i_{t|t+1} = \beta^i_t Z^i_t \tag{37}$$

where Z_t^i is a vector of fundamental factors that individual i uses to generate her

forecast and β_t^i is a vector of weights attached to them. According to (37),

movements in $\hat{P}_{t|t+1}^i$ occur because of movements in fundamentals that individual

i deems relevant in her forecasting, Z_t^i, and the revisions in the individuals'

forecasting strategy, that is, changes in the betas:[32]

$$\hat{P}_{t|t+1}^i - \hat{P}_{t-1|t}^i = \Delta\beta_t^i Z_t^i + \beta_{t-1}^i \Delta Z_t \qquad (38)$$

where Δ is the first difference operator and $\Delta\beta_t^i$ may involve changes in the set of

causal variables used in forecasting.

IKE recognizes that such change is to a significant extent non-routine. The

changes in the causal variables depend on changes in policy, new technology,

and other changes in the social context. Changes in betas reflect new ways of

thinking which may depend on psychological considerations, such as optimism

and confidence. We would not expect such change to conform to mechanical

rules. However, IKE explores the possibility that change nonetheless exhibits

regularities which are qualitative and contingent.

1.4.5.1 Fully Predetermined Policy Environment

Although, in general, we would expect the process governing the causal

factors to change in non-routine ways, the IKE model assumes a fully

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[32] From (37), adding and subtracting $\beta_{t-1}^i Z_t^i$ from the change in the point forecast yields, $\hat{P}_{t|t+1}^i - \hat{P}_{t-1|t}^i = \beta_t^i Z_t^i - \beta_{t-1}^i Z_{t-1}^i + \left(\beta_{t-1}^i Z_t^i - \beta_{t-1}^i Z_t^i\right)$. It follows that $\hat{P}_{t|t+1}^i - \hat{P}_{t-1|t}^i = \Delta\beta_t^i Z_t^i + \beta_{t-1}^i \Delta Z_t^i$.

predetermined process. The causal factors are assumed to follow a random walk with drift: [33]

$$\Delta Z_t^i = \varphi^{Z^i} + \varepsilon_t^i \tag{39}$$

where φ^{Z^i} and ε_t^i are vectors of drift and error terms respectively. This assumption allows IKE models to focus attention on revisions in forecasting behavior.[34]

1.4.5.2 Revisions in Forecasting Strategies

The vast majority of extant models, including the canonical and bubble models sketched above, address the problem of change by assuming it away: they fix the betas and assume that individuals use the same forecasting strategy at every point in time. The relatively few models that do allow for change do so in a fully predetermined way.[35] But, in general, we would expect revisions in market participants' forecasting strategies to undergo non-routine change.[36]

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[33] Much evidence supports the assertion that fundamental factors thought to influence financial markets, such as earnings, interest rates and income, can be characterized as following an I(1) process with drift. See Juselius (2007) for details.

[34] The model could be generalized to include an IKE process for the causal factors. But, one would need to ask what qualitative and contingent regularities we would expect to see in change in policy and the process governing the causal factors.

[35] For example, models which follow a regime-switching Marchov process allow for change but in a fully predetermined way. See Hamilton (1994) for details. Other examples of changing strategies include behavioral models where individuals change the weights they place on fundamental and technical trading considerations. See, for example, Frankel and Froot (1987) and De Grauwe and Grimaldi (2006).

[36] The narrative account of Shiller (2000b, 2005) and Akerlof and Shiller (2009) is consistent with this view. In their qualitative account of stock price swings, psychological considerations, or "Animal Spirits", play an intermediating role between fundamentals and individuals beliefs about future outcomes. And, because their model rests on a qualitative structure change amongst the causal process and individual behavior does not conform to any mechanical rule.

To represent changes in forecasting strategies, IKE models formalize an insight from Keynes (1936, p. 152). In describing how market participants will change the way that they think about the future, Keynes notes that individuals will,

> 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 recognized that market participants tend to stick with a current forecasting strategy unless they see reason to deviate from it.

Fydman and Goldberg's IKE model incorporates this insight with a qualitative and contingent regularity they call "guardedly moderate" revisions in individual forecasting strategies. This regularity presumes that unless individuals have a reason to change their forecasting strategies, they will adhere to their existing strategy or only alter it in a gradual fashion. To be sure, individuals' decision to change, or revise, the way that they think about the future depends on many factors, such as the past performance of different forecasting strategies, the social context, psychological and emotional considerations, institutional changes as well as the gap from benchmark levels. Even if an individual does decide to change her forecasting strategy, it is not clear in an IKE model *what* to change and *how* to change it.

To specify more formally how to represent the qualitative regularity of guardedly moderate revisions, we need to identify some baseline, or reference point, that individuals may use as a yardstick with which to alter their thinking of the future against. To see this, note that, given (39), (38) may be rewritten as,

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$$\hat{P}^i_{t|t+1} - \hat{P}^i_{t-1|t} = \mathcal{H}\hat{P}^i_{t|t+1} + \varepsilon^i_t \tag{40}$$

where $\mathcal{H}\hat{P}^i_{t|t+1}$ denotes the "trend change" in an individual's forecast from period *t-1* to *t*:

$$\mathcal{H}\hat{P}^i_{t|t+1} = \Delta\beta^i_t Z^i_t + \beta^i_{t-1}\varphi^{Z^i} \tag{41}$$

Like equation (38), movements in the "trend change" depend on revisions in forecasting strategies, $\Delta\beta^i_t$, and on the "baseline drift", $\beta^i_{t-1}\varphi^{Z^i}$, of forecasts based on actual trends in fundamental factors.

Even if an individual fails to revise her forecasting strategy between *t-1* and *t*, suggesting $\Delta\beta^i_t Z^i_t = 0$, she would tend to alter her point forecast $\hat{P}^i_{t|t+1}$ because the fundamentals would tend to move in persistent directions as portrayed by the drift in these variables. In this case, the individuals' point forecast would tend to move in one direction or the other, depending on the algebraic sign of $\beta^i_{t-1}\varphi^{Z^i}$.

The individual may revise her strategy, which would either reinforce or impede the impact of the baseline drift. But, if the revision is small enough or guardedly moderate, the trend change in $\hat{P}^i_{t|t+1}$ will be determined by the baseline drift in the fundamental factors.

To formalize this reasoning, the IKE model makes use of two *qualitative* restrictions,

$$\left|\Delta\beta^i_t Z^i_{t-1}\right| < \theta^i_t \tag{42}$$

$$\left|\Delta\beta^i_{t-1}\varphi^{Z^i}\right| < \theta^i_t \tag{43}$$

where $\theta_t^i = \left| \beta_{t-1}^i \varphi^{z^i} \right|$ is the absolute value of the baseline drift. The first qualitative condition implies that from *t-1* to *t*, any revisions in betas will not outweigh the impact of the baseline drift in the change in $\hat{P}_{t|t+1}^i$. The second qualitative condition ensures that any change in the betas at *t* does not alter the sign of the baseline drift. The idea behind equations (42) and (43) is that as long as individuals' revise their forecasting strategies in moderate ways, then trends in fundamental factors will tend to dominate movements in $\hat{P}_{t|t+1}^i$.

IKE models recognize that such change in forecasting strategies is contingent. The regularity of guardedly moderate revisions in the way individuals think about the future does not follow any fixed rule; it may become uneven or even cease to exist at various times that are unpredictable and cannot be specified in advance. This feature of IKE models allows for swings in $\hat{P}_{t|t+1}^i$ to be uneven and undergo reversals at unforeseen times. However, in any period where this regularity does hold, we would get a swing in $\hat{P}_{t|t+1}^i$.

1.4.5.3 Swings in Market Prices

IKE models represent equilibrium in asset markets as an aggregation of the total buying and selling decisions of bulls and bears. The IKE model recognizes that there is great diversity of views among individuals regarding how to think about future market outcomes. The model allows for bulls, who predict prices to increase,

$$\hat{P}_{t|t+1}^{i,L} - P_t > 0 \tag{44}$$

and bears, who predict prices to fall,

$$\hat{P}_{t|t+1}^{i,S} - P_t < 0 \qquad (45)$$

To formulate a representation of the market's forecast, IKE aggregates over the wealth shares of all bulls and bears:[37]

$$\hat{P}_{t|t+1} = \frac{1}{2}\left(\hat{P}_{t|t+1}^{i,L} + \hat{P}_{t|t+1}^{i,S}\right) = \beta_t Z_t \qquad (46)$$

where Z_t is the pool of all causal factors that individuals use to formulate their forecasts and β_t are the average coefficients that individuals attach to these factors.

For any individual, bull or bear, future changes in $\hat{P}_{t|t+1}^i$ will depend on the sign of the initial baseline drift, $\beta_{t-1}^i \varphi^{Z^i}$. If $\beta_{t-1}^i \varphi^{Z^i} > 0$ and individuals revise their forecasts in moderate ways, the change in their forecast will remain positive, leading to an increase in $\hat{P}_{t|t+1}^i$ over the period. Positive trends in informational variables, such as earnings and overall economic activity, whether for a bull or bear, would lead to a rise in $\hat{P}_{t|t+1}^i$; even though a bear predicts $\hat{P}_{t|t+1}^i < P_t$ she may become less bearish over the period.

If guardedly moderate revisions in forecasting strategies and trends in informational variables lead all participants to bid $\hat{P}_{t|t+1}^i$ in the same direction then (40) implies that $\hat{P}_{t|t+1}$, and thus P_t, will undergo a swing in the same direction. But, since individuals' revisions in forecasting strategies are not always moderate, swings in $\hat{P}_{t|t+1}$ are irregular; there may be periods where individuals alter the way they think about the future in dramatic ways. The IKE model of price

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[37] The IKE model assumes that wealth shares are constant and exogenous to the model and as such, are equal to a half.

swings and risk suggests that this may occur and lead to reversals in $\hat{P}_{t|t+1}$ and ultimately in P_t.

IKE models of price swings and risk generate swings in P_t through swings in $\hat{P}_{t|t+1}$. Unlike the bubble models, swings in $\hat{P}_{t|t+1}$ arise due to trends in fundamentals, but psychology is important too. This implies that changes in $\hat{P}_{t|t+1}$ and thus P_t, are non-routine.

1.5 Conclusion

This chapter showed that the bubble and IKE models both explain swings through the market's expectation $\hat{P}_{t|t+1}$. The models, however, differ in how they represent short-term movements in $\hat{P}_{t|t+1}$ which take prices away from and toward benchmark levels. The bubble models posit that swings in $\hat{P}_{t|t+1}$ are driven by psychological and technical momentum-related considerations. IKE models, on the other hand, explain price swings in $\hat{P}_{t|t+1}$ through persistent trends in fundamentals, although psychological considerations are also important. The next chapter introduces the empirical methodologies employed in Chapters 3 through 5 to confront the competing implications of bubble and IKE models.

Appendix

A1.1: Proof that $g < r^f$ is Necessary for the Traditional Gordon Growth Model

A1.1 Proof

To see why the assumption that $g < r^f$ is necessary for the Gordon growth model, we start with the present value equation:

$$P_t = E_t \sum_{i=1}^{\infty} \frac{D_{t+i}}{\left(1+r^f\right)^i} \tag{A1}$$

The market's expectation for the dividend process can be written as:

$$E_t[D_{t+i}] = (1+g)^i D_t \tag{A2}$$

Plugging (A2) into (A1) yields,

$$P_t = \sum_{i=1}^{\infty} \frac{(1+g)^i D_t}{\left(1+r^f\right)^i} \tag{A3}$$

which may be rewritten as,

$$P_t = \left[\sum_{i=1}^{\infty} \left(\frac{1+g}{1+r^f}\right)^i\right] D_t \tag{A4}$$

If $g < r^f$ then the term in brackets in (A4) may be rewritten as:

$$\sum_{i=1}^{\infty} \left(\frac{1+g}{1+r^f}\right)^i = \frac{1+g}{r^f-g} \tag{A5}$$

To prove this, multiply both sides of (A5) by $\left(1 - \frac{1+g}{1+r^f}\right)$ to yield,

$$\left(1 - \frac{1+g}{1+r^f}\right) \sum_{i=1}^{\infty} \left(\frac{1+g}{1+r^f}\right)^i = \left(1 - \frac{1+g}{1+r^f}\right) \frac{1+g}{r^f-g} \tag{A6}$$

or,

$$\sum_{i=1}^{\infty} \left(\frac{1+g}{1+r^f}\right)^i - \sum_{i=1}^{\infty} \left(\frac{1+g}{1+r^f}\right)^{i+1} = \left(1 - \frac{1+g}{1+r^f}\right) \frac{1+g}{r^f-g} \tag{A7}$$

Simplifying (A7) gives us,

$$\left(\frac{1+g}{1+r^f}\right) + \left(\frac{1+g}{1+r^f}\right)^2 + \left(\frac{1+g}{1+r^f}\right)^3 + \cdots$$

$$-\left(\frac{1+g}{1+r^f}\right)^2 - \left(\frac{1+g}{1+r^f}\right)^3 - \left(\frac{1+g}{1+r^f}\right)^4 - \cdots$$

$$= \left(\frac{r^f-g}{1+r^f}\right)\frac{1+g}{r^f-g} \tag{A8}$$

or,

$$\frac{1+g}{1+r^f} = \frac{1+g}{1+r^f} \qquad \text{Q.E.D.} \tag{A9}$$

A1.2: Microfoundations of IKE Models: Endogenous Prospect Theory

A1.2.1 Introduction

There is much research which suggests that when faced with gambles involving uncertain outcomes, individuals' actual decision behavior is inconsistent with traditional probability theory and risk aversion as defined under the axioms of the expected utility hypothesis (Kahneman and Tversky, 1979 and Tversky and Kahneman, 1992).

The experimental findings of Kahneman and Tversky – which constitute the core assumptions of prospect theory – imply that individuals' actual behavior when faced with gambles involving uncertain payoffs exhibit the following three characteristics: (1) *loss aversion* – individuals' utility function is steeper (convex) in the domain of losses than in the domain of gains (concave); this implies that individuals derive greater disutility over losses than of gains of the same magnitude, (2) *reference dependence* – individuals' utility is defined in terms of

gains and losses in wealth relative to some reference point, as opposed to an individuals' absolute *level* of wealth and (3) *diminishing sensitivity* – individuals' marginal utility decreases with the magnitude of gains and losses.

In representing individuals' preferences over gambles, prospect theory replaces the probabilities of outcomes employed by expected utility theory with decision weights defined as the weighted sum of values of all individual outcomes.

In modeling individuals' preferences over gambles with uncertain outcomes, IKE has built upon the foundations of prospect theory to develop Endogenous Prospect Theory (EPT). In addressing the proposition of individual loss aversion, EPT posits that there exists a positive relationship between the degree of loss aversion exhibited by an individual and the size of their speculative position. The latter is determined by the individuals' forecast of potential losses and is, therefore, dubbed *endogenous loss aversion*. And because IKE represents individual forecasting behavior in only a partially predetermined fashion, the degree of loss aversion and thus individual preferences are also partially predetermined.

IKE also replaces the decision weighted sums of values of single outcomes with forecasting strategies that depend on expected returns and potential losses in the marketplace. This implies that individuals will demand a minimum market premium – or expected return – which is positively related to an individual's potential loss. IKE calls this premium the individual *uncertainty premium*. Consider the following IKE model of EPT.

A1.2.2 Endogenous Prospect Theory

Assume individuals may hold nonmonetary wealth in the form of a risky asset, stocks, and a risk-free asset, bonds. As a result, the total nonmonetary wealth for individual i entering time t can be defined as:

$$W_t^i = S_t^i + B_t^i \qquad i = 1, \ldots, N \qquad (A10)$$

where W_t^i denotes individual i's real nonmonetary wealth at time t and S_t^i and B_t^i are the real value of stocks and bonds held by individual i entering period t, respectively. The *ex post* nominal return on stocks expressed in logarithmic form is:

$$R_{t+1} = P_{t+1} - P_t - r_t^f \qquad (A11)$$

where P_t is the log of the stock price at time t and r_t^f is the risk-free nominal return on bonds. Let a_t^i equal the size of the individual's open position in stocks where $a_t^i > 0$ $\left(a_t^i < 0\right)$, defines the individual as a net demander (seller) of stocks. Equation (A10) may then be written as:

$$W_t^i = a_t^i W_t^i + \left(1 - a_t^i\right) W_t^i \qquad \text{for } i = 1, \ldots, N \qquad (A12)$$

Given the individual's portfolio allocation between stocks and bonds, her wealth at time $t + 1$ is determined by the real return from both assets,

$$W_{t+1}^i = S_t^i \left(P_{t+1} - P_t - r_t^f - \pi_t\right) + B_t^i \left(1 + r_t^f - \pi_t\right) \quad \text{for } i = 1, \ldots, N \qquad (A13)$$

where π_t is the non-stochastic inflation rate. From A(12) and (A13) individual i's wealth at time t may be written as:

$$W_{t+1}^i = a_t^i W_t^i \left(P_{t+1} - P_t - r_t^f\right) + W_t^i \left(1 + r_t^f - \pi_t\right) \quad \text{for } i = 1, \ldots, N \qquad (A14)$$

Loss averse individuals derive greater disutility from losses than utility from gains of the same magnitude. Following prospect theory, EPT measures gains and losses relative to some reference level. Consider the following change in an individual's wealth from period t to $t + 1$ as:[38]

$$\Delta W_{t+1}^i = W_t^i \left[a_t^i R_{t+1} + (1 + i_t - \pi_t) \right] - \Gamma_t^i \tag{A15}$$

where Γ_t^i is the reference level for individual i (defined below), and Δ is the first difference operator. If $\Delta W_{t+1}^i > 0$ $\left(\Delta W_{t+1}^i < 0 \right)$, the individual is said to incur a gain (loss). In determining the reference point, if the individual were to stay out of the market completely they could earn a riskless real return on bonds equal to $r_t^f - \pi_t$. As such, the individual's level of reference can be represented as,

$$\Gamma_t^i = W_t^i (1 + i_t - \pi_t) \tag{A16}$$

By substituting (A16) into (A15) it follows that, relative to the individual's reference level, the one-period change in her total wealth can be expressed as:

$$\Delta W_{t+1}^i = a_t^i W_t^i R_{t+1} \tag{A17}$$

A positive outcome for R_{t+1}, expressed as r_{t+1}^+, results in a gain for an individual holding a long position in stocks ($a_t^i > 0$), and a loss from holding a short position($a_t^i < 0$). Conversely, a negative result for R_{t+1}, expressed as r_{t+1}^-, leads to a gain for an individual holding a short position in stocks ($a_t^i < 0$), and a loss if she holds a long position ($a_t^i > 0$). Individuals which hold long and short positions in stock are commonly referred to as bulls and bears, respectively.

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[38] Since $S_t^i = a_t^i W_t^i$ and $B_t^i = \left(1 - a_t^i \right) W_t^i$ we can write (A13) as
$$W_{t+1}^i = a_t^i W_t^i \left(P_{t+1} - P_t - r_t^f - \pi_t \right) + \left(1 - a_t^i \right) W_t^i \left(1 + r_t^f - \pi_t \right)$$
$$= W_t^i \left[1 + a_t^i \left(P_{t+1} - P_t - r_t^f - \pi_t \right) + \left(1 - a_t^i \right) \left(r_t^f - \pi_t \right) \right]$$
$$= W_t^i \left[a_t^i R_{t+1} + \left(1 + r_t^f - \pi_t \right) \right]$$

Kahneman and Tversky refer to all potential values for the changes in wealth, ΔW_{t+1}^i, as prospects. Under prospect theory, an individual considers which set of prospects and corresponding weights to attach to them in making her speculative decisions. To represent an individual's preferences under prospect theory, the economist must specify the individual prospects and corresponding decision weights she attaches to them.

I follow Frydman and Goldberg (2007, 2012) in assuming that the individual only considers a finite set of prospects. She attaches a corresponding weight to each prospect and considers her utility from aggregating all prospects; this is her prospective utility.

Frydman and Goldberg (2007, 2012) develop EPT by specifying the following utility function:

$$V(\Delta W) = \begin{cases} (W|a|)^{\alpha}|r^g| & if\ \Delta W > 0 \\ -\lambda_1(W|a|)^{\alpha}|r^l| - \frac{\lambda_2}{-\hat{\Pi}(\hat{r}^-)}(W|a|)^{\alpha+1}|r^l| & if\ \Delta W < 0 \end{cases} \quad (A18)$$

where $\lambda_1 > 1$ and $\lambda_2 > 0$, $\hat{\Pi}(\cdot)$ denotes the decision weighted sums of prospects, a is positive (negative) for a bull (bear) and,

$$r^g = r_{t+1}^+, r^l = r_{t+1}^- \quad \text{for a bull} \quad (A19)$$

$$r^g = -r_{t+1}^-, r^l = -r_{t+1}^+ \quad \text{for a bear}$$

The degree of loss aversion that follows equation (A19) is:

$$\Lambda = \lambda_1 + \lambda_2(W|a|) \quad (A20)$$

The linear prospective utilities based on the utility function in (A18) for long (L) and short (S) positions, respectively are:

$$PU_t^L = (a_t W_t)^{\alpha}\left[\hat{\Pi}(\hat{r}) - (1-\lambda)\hat{\Pi}(\hat{r}^-)\right] + \lambda_2(a_t W_t)^{\alpha+1}\hat{\Pi}(\hat{r}^-) \quad (A21)$$

and

$$PU_t^S = (-a_t W_t)^\alpha \left[\hat{\Pi}(\hat{r}) - (1-\lambda)\hat{\Pi}(-\hat{r}^+) \right] + \lambda_2 (a_t W_t)^{\alpha+1} \hat{\Pi}(-\hat{r}^+) \quad \text{(A22)}$$

where the decision-weighted sums of the prospects are,

$$\hat{\Pi}(\hat{r}) = \sum_k^{K^+} w_{t|t+1,k}^i \hat{r}_{t|t+1,k} \quad \text{(A23)}$$

$$\hat{\Pi}(\hat{r}^-) = \sum_k^{K^-} w_{t|t+1,k}^{i-} \hat{r}^-_{t|t+1,k} \quad \text{(A24)}$$

where w^i are the individual decision weights.

Each individual at time t faces the decision problem of choosing the portfolio allocation, a_t^i, which maximizes her prospective utilities given her assessments of expected losses and gains from holding a speculative position in stock. Since the prospective utilities in (A21) and (A22) are only for given values of $a_t^i \geq 0$ and $a_t^i \leq 0$, respectively, the individual faces two separate choice decisions; one for long positions (A21) and one for short position (A22). To solve her decision problem, she must, therefore, differentiate both (A21) and (A22) with respect to a_t^i, which yields,

$$a_t^L = \frac{\alpha}{\lambda_2(\alpha+1)W} \left[\hat{\Pi}(\hat{r}) - (1-\lambda)\hat{\Pi}(\hat{r}^-) \right] \quad \text{(A25)}$$

$$-a_t^S = \frac{\alpha}{\lambda_2(\alpha+1)W} \left[\hat{\Pi}(\hat{r}) - (1-\lambda)\hat{\Pi}(-\hat{r}^+) \right] \quad \text{(A26)}$$

I follow Frydman and Goldberg (2007, 2012) by replacing the decision-weighted sums, $\hat{\Pi}(\cdot)$, with forecasts of potential returns and losses:

$$a_t^L = \frac{1}{\lambda_3 W} \left[\hat{r}_{t|t+1}^L - (1-\lambda)\hat{l}_{t|t+1}^L \right] \quad \text{(A27)}$$

$$-a_t^S = \frac{1}{\lambda_3 W} \left[\hat{r}_{t|t+1}^S - (1-\lambda)\hat{l}_{t|t+1}^S \right] \quad \text{(A28)}$$

where $\lambda_3 = \frac{\lambda_2(1+\alpha)}{\alpha}$, $\hat{r}^L_{t|t+1}$ ($\hat{r}^S_{t|t+1}$) are the bull's (bear's) forecasts of the potential

return and $\hat{l}^L_{t|t+1}$ ($\hat{l}^S_{t|t+1}$) are the bull's (bear's) forecasts of the potential unit

losses, where,

$$\hat{l}^{i,L}_{t|t+1} = E^i_t\left[r^L_{t+1} < 0 | Z^i_t\right] < 0 \qquad (A29)$$

and

$$\hat{l}^{i,S}_{t|t+1} = E^i_t\left[r^S_{t+1} < 0 | Z^i_t\right] < 0 \qquad (A30)$$

Equations (A27) and (A28) imply that, under EPT, individuals limit the

amount of capital they wager when assessing a profit opportunity. Individuals will

hold open positions only when the forecasted potential return exceeds the

forecasted potential unit losses given their degree of endogenous loss aversion.

These representations of the size of stake in stock imply the following decisions

rules:

- Stay out of the market when $\hat{r}^L_{t|t+1} \leq (1-\lambda)\hat{l}^L_{t|t+1}$ and $\hat{r}^S_{t|t+1} \leq \hat{l}^S_{t|t+1}$

- Hold a long position in stock the size of $a^L_t W_t$ when $\hat{r}^L_{t|t+1} > (1-\lambda)\hat{l}^L_{t|t+1}$ or

- Hold a short position in stock of size $-a^S_t W_t$ when $\hat{r}^S_{t|t+1} > (1-\lambda)\hat{l}^S_{t|t+1}$

The representations derived above for individual preferences under EPT

lead to three significant implications for endogenous loss aversion and

speculative behavior in the stock market. First, if and when an individual decides

to take a speculative position in the market she takes one of limited size. This is

a consequence of the degree of loss aversion she possesses.

Second, even though a bull's (bear's) forecast of potential returns is

positive, i.e. $\hat{r}^L_{t|t+1} > 0$ ($\hat{r}^S_{t|t+1} > 0$), her degree of loss aversion, λ_1, and her

forecast of potential unit losses, $\hat{l}^L_{t|t+1}$ ($\hat{l}^S_{t|t+1}$) may be large enough that she decides to stay out of the market.

Third, EPT and equations (A27) and (A28) imply that individuals require an *uncertainty premium* in order to compensate them for their potential unit losses from holding a speculative position in stock which is equal to,

$$\widehat{up}^{L,i}_{t|t+1} = (1 - \lambda)\hat{l}^{L,i}_{t|t+1} > 0 \tag{A31}$$

$$\widehat{up}^{S,i}_{t|t+1} = (1 - \lambda)\hat{l}^{S,i}_{t|t+1} > 0 \tag{A32}$$

A1.2.3 Momentary Equilibrium in the Stock Market

Equilibrium in the stock market is achieved when the following condition is satisfied,

$$\sum_{i=1}^{N}\left(D^i_t - S^i_t\right) = D_t - S_t = 0 \tag{A33}$$

where D^i_t denote individual demand for stock, where $D^i_t = a^i_t W_t$, and S^i_t represents the individual supply of stock entering period t. The values D_t and S_t denote the aggregate market demand and supply of stock, respectively. We note that given the optimal portfolio allocation of stock from (A27) and (A28), there still may exist those individuals with positive market wealth but nonetheless decide to stay out of the market. Given these nonzero wealth-holders, we can now substitute equations (A27) and (A28) into the definition of momentary equilibrium in (A33):

$$\sum_{i=1}^{N^L}\left[\frac{1}{\lambda_3}\left(\hat{r}^{L,i}_{t|t+1} - (1-\lambda)\hat{l}^{L,i}_{t|t+1}\right)W^{L,i}_t - S^{L,i}_t\right]$$

$$+ \sum_{i=1}^{N^S}\left[\frac{1}{\lambda_3}\left(\hat{r}^{S,i}_{t|t+1} - (1-\lambda)\hat{l}^{S,i}_{t|t+1}\right)W^{S,i}_t - S^{S,i}_t\right] + \sum_{i=1}^{N^O}\left[0 - S^{O,i}_t\right] = 0 \tag{A34}$$

where O denotes all nonzero wealth holders who are not in the market and $N^L(N^S)$ are the number of individuals holding long (short) positions in stock at time t. Multiplying (A34) by λ_3 and dividing by total wealth in the market at time t, W_t^M, we get,

$$\sum_{i=1}^{N^L}\left[\left(\hat{r}_{t|t+1}^{L,i} - (1-\lambda)\hat{l}_{t|t+1}^{L,i}\right)\frac{W_t^{L,i}}{W_t^M} - \lambda_3 \frac{S_t^{L,i}}{W_t^M}\right]$$

$$+ \sum_{i=1}^{N^S}\left[\left(\hat{r}_{t|t+1}^{S,i} - (1-\lambda)\hat{l}_{t|t+1}^{S,i}\right)\frac{W_t^{S,i}}{W_t^M} - \lambda_3 \frac{S_t^{S,i}}{W_t^M}\right] + \sum_{i=1}^{N^O}\left[O - \lambda_3 \frac{S_t^{O,i}}{W_t^M}\right] = 0 \text{ (A35)}$$

Equation (A35) may be aggregated over all individuals and rewritten as,

$$\left[\frac{W_t^L}{W_t^M}\hat{r}_{t|t+1}^L - \frac{W_t^S}{W_t^M}\hat{r}_{t|t+1}^S\right] - (1-\lambda_1)\left[\frac{W_t^L}{W_t^M}\hat{l}_{t|t+1}^L - \frac{W_t^S}{W_t^M}\hat{l}_{t|t+1}^S\right] = \lambda_3 \frac{S_t^O}{W_t^M} \quad \text{(A36)}$$

Equation (A36) may be rewritten by letting,

$$\hat{r}_{t|t+1} = \frac{W_t^L}{W_t^M}\hat{r}_{t|t+1}^L - \frac{W_t^S}{W_t^M}\hat{r}_{t|t+1}^S \tag{A37}$$

$$\widehat{up}_{t|t+1} = (1-\lambda_1)\left[\frac{W_t^L}{W_t^M}\hat{l}_{t|t+1}^L - \frac{W_t^S}{W_t^M}\hat{l}_{t|t+1}^S\right] \tag{A38}$$

$$\widehat{up}_{t|t+1}^L = \frac{W_t^L}{W_t^M}\hat{l}_{t|t+1}^L \tag{A39}$$

$$\widehat{up}_{t|t+1}^S = \frac{W_t^S}{W_t^M}\hat{l}_{t|t+1}^S \tag{A40}$$

Using equations (A31) and (A32) and (A37)-(A40), we can now write an expression relating the market's aggregate forecast of returns to the market premium,

$$\hat{r}_{t|t+1} = \widehat{pr}_{t|t+1} \tag{A41}$$

where,

$$\widehat{pr}_{t|t+1} = \widehat{up}_{t|t+1} + \lambda_3 \frac{S_t}{W_t^M} \tag{A42}$$

Equations (A41) and (A42) express momentary equilibrium in the stock market. This condition implies that the market premium is determined by the uncertainty premium, i.e. the relative forecasted potential unit losses for bulls and bears scaled by their degrees of loss aversion, plus the ratio of total supply of stock to total market wealth. Market equilibrium is achieved when the aggregate market forecast for potential returns equals the expected market premium.

A1.2.4 Equilibrium Price for the Stock Market and the Gap Effect

Recall that the *ex ante* return on a long position in stocks is,

$$\hat{r}_{t|t+1} = \hat{P}_{t|t+1} - P_t - r_t^f \tag{A43}$$

Using equations (A29) and (A30) and holding interest rates and relative asset supplies constant, yields,

$$P_t = \hat{P}_{t|t+1} - (1 - \lambda)\hat{l}_{t|t+1} \tag{A44}$$

Like most extant models of asset prices, market expectations play an integral role. In this framework the primary drivers of stock price movements are forecasts of stock prices, $\hat{P}_{t|t+1}$, and potential unit losses, $\hat{l}_{t|t+1}$.

In specifying the uncertainty premium, IKE models invoke an insight from Keynes (1936, p. 201) who noted that, when taking a speculative position, individuals' assessments of risk depend on the deviation of prices from estimates of "safe" levels. IKE models formalize this insight by connecting an individual's forecast of her potential unit loss to the gap between current prices and some estimate of common benchmark levels.

To see this, consider a stock price that has increased beyond estimates of common benchmark values. As the market's assessment of the gap increases, bulls and bears contemplate greater and smaller respective potential losses from speculation. To compensate the bulls for the elevated riskiness of their open positions, their uncertainty premiums rise while those of the bear's fall. These two forces contribute to an overall rise in the aggregate market premium. Extending this insight to an individual's assessment of potential unit losses implies,[39]

$$\hat{l}^i_{t|t+1} = \hat{l}_{t|t+1}\left(\widehat{gap}^i_{t|t+1}\right) \tag{A45}$$

where $\widehat{gap}^i_{t|t+1} = P_t - \hat{P}^{i,BM}_{t|t+1}$. Here, $\hat{P}^{i,BM}_{t|t+1}$ captures the individual forecast of some estimate of an historical benchmark level. How individuals interpret the gap and its impact on potential unit loss and assessments of risk changes over time in ways that no one can fully foresee. In this light, changes over time in the relationship between gap considerations and the potential unit loss are modeled in a *partially* predetermined fashion for bulls and bears, respectively, as[40],

$$\frac{\Delta \hat{l}^{i,L}_{t|t+1}}{\Delta \widehat{gap}^i_{t|t+1}} < 0 \quad \text{and} \quad \frac{\Delta \hat{l}^{i,S}_{t|t+1}}{\Delta \widehat{gap}^i_{t|t+1}} > 0 \tag{A46}$$

By only partially predetermining how change unfolds over time, this representation allows for a myriad of possible probability distributions that govern individual forecasting behavior, recognizing the importance of non-routine change. This framework implies the following expression for the market premium,

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[39] For an individual taking a pure long position in stocks, the expected unit loss, $\hat{l}^{i,L}_{t|t+1}$, given the set of informational causal variables, Z^i_t, is $\hat{l}^{i,L}_{t|t+1} = E^i_t\left[r^L_{t+1} < 0 | Z^i_t\right] < 0$. Conversely, for an individual taking a short position, her expected unit loss is, $\hat{l}^{i,S}_{t|t+1} = E^i_t\left[r^S_{t+1} < 0 | Z^i_t\right] < 0$.

[40] Note that the inequalities arise from the fact that unit losses are defined as negative values (see equations A29 and A30).

$$\widehat{pr}_{t|t+1} = \sigma_t\left(P_t - \hat{P}_{t|t+1}^{BM}\right) \tag{A47}$$

where $\sigma_t > 0$ and $\frac{\Delta \widehat{pr}_{t|t+1}}{\Delta \widehat{gap}_{t|t+1}} > 0$. This leads to the following equilibrium expression

for the aggregate stock market price,

$$P_t = P_t^{BM} + \left(\frac{1}{1+\sigma_t}\right)\left(\hat{P}_{t|t+1} - \hat{P}_{t|t+1}^{BM}\right) \tag{A48}$$

CHAPTER II

METHODOLOGICAL APPROACHES TO EMPIRICALLY TESTING THE COMPETING IMPLICATIONS OF BUBBLE AND IKE MODELS

2.1 Introduction

Chapter 1 cast the alternative classes of models – canonical, bubble and IKE – within a composite theoretical framework. In contrast to the canonical model, bubble and IKE models explain swings in stock prices away from and back towards benchmark levels through autonomous movements in the market's expectation of future prices. Chapter 1 showed that both classes of models portray contrasting behavior of market participants in formulating shorter-term price forecasts. Bubble models imply that pure psychological and momentum-related considerations underpin shorter-term stock price movements. IKE models, on the other hand, argue that trends in fundamentals are the primary driver of shorter-term price fluctuations but, because of imperfect knowledge, this relationship changes at times and in ways that would be difficult to adequately capture with an overarching mechanical rule.

It appears difficult to confront the competing implications of bubble and IKE models with empirical evidence. How can we test the bubble models implications that purely psychological and technical momentum-related considerations are the primary driver of stock price fluctuations when such factors are difficult to measure let alone incorporate in statistical analysis? How

can we test the IKE implications that fundamental stock-price relationships are temporally unstable?

The purpose of this chapter is to provide the methodological context in which I confront the alterative classes of models with empirical evidence in Chapters 3 through 5. These chapters make use of two different approaches. Chapter 3 constructs and analyzes a novel dataset based on information contained in *Bloomberg News'* (end-of-the-day) equity market wraps. The textual data compiled from these reports provide relative measures of the importance of psychological and technical trading considerations. In addition, they allow for the measurement of the importance of fundamental factors even though they may matter in non-routine ways.[41]

Chapters 4 and 5 make use of more formal econometric analysis to investigate the temporal stability of stock-price relations and the extent to which fundamentals matter for stock price fluctuations, respectively. In conducting such analysis, however, it is often unclear which specific measures of certain variables to include when bridging the gap between theory and econometric specification. For example, if testing the implications of the present value model, which measure of expected cash flows is the better candidate: dividends or earnings? Similarly, which is the most appropriate measure of interest rates used in discounting these cash flows: bills, notes or bonds?

Indeed, when confronted with this task, empirical researchers – searching for a greater understanding of the factors which market participants actually

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[41] The term "non-routine" refers to changes in the causal process which underpin market outcomes that would be difficult to capture with an overarching mechanical rule.

deem relevant in formulating their trading decisions – are often provided very little in the way of guidance. To address this issue, Chapters 4 and 5 use the *Bloomberg* analysis as a guide in specifying the econometric model.

The chapter is organized as follows. Section 2 introduces the methodological approach to the descriptive analysis based on the *Bloomberg* data. Section 3 presents the econometric approaches followed in subsequent chapters and the rationale for incorporating results from the *Bloomberg* analysis.

2.2 The Methodological Approach to the *Bloomberg* Analysis

This subsection introduces the *Bloomberg* data and methodology utilized. The aim is to set the context for the analysis in Chapter 3 where a more detailed description is provided.

2.2.1 Methodology in Constructing the *Bloomberg* Data

The analysis of Chapter 3 is based on the information contained in *Bloomberg News'* (end-of-the-day) equity market wraps over the sample period January 4, 1993 through December 31, 2009. The *Bloomberg* equity market journalists receive information about the day-to-day market movements from two sources within each wrap. The first source entails *Bloomberg* equity market analysts. With a wealth of information regarding economic, political, international, and social goings-on, the market analysts track up-to-the-minute market behavior. The second source involves surveys of a revolving cohort of 100-200 equity fund managers whose testimony is provided in every market wrap.

The textual data is based on keeping track of the factors that the daily wrap stories report as underpinning the day's aggregate stock price movement. Each of the approximately 120 factors tracked are recorded with a (+/-) 1 depending on the reported directional relationship with the stock price,[42] given the market's expectation, while all other factors are given a zero. The frequencies with which the separate factors are found to drive daily prices and their directional relationship are then aggregated into three main categories: fundamental, technical and psychological.

One stage of analysis looks at the overall frequency with which a factor was reported to merit the attention of market participants over the seventeen year period. A second stage looks at a monthly factor frequency: the number of days which a factor was reported as driving the aggregate stock market as a proportion of total trading days per month.

Investigating the overall and monthly factor frequencies provides a method for confronting the competing implications of bubble and IKE models on the basis of the relative importance of fundamental, psychological and technical momentum-related considerations. But, IKE models also imply that fundamentals matter for stock prices in non-routine ways: different fundamentals matter in different ways during different time periods. The textual data enable me to investigate this conjecture in two ways. First, I examine how fundamentals' monthly factor frequencies vary over time. Second, I look at whether fundamental

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[42] A + (-) 1 denotes a positive (negative) relationship between the causal factor and the stock market price given the market's expectation. See Chapter 3 for a more detailed discussion on this and the problem of actual versus expected changes in such factors.

factors' directional relationships with stock prices shift from one time period to another.

2.2.2 Benefits of *Bloomberg* Data

There are several benefits to the textual data based on the *Bloomberg* market wraps. Because the *Bloomberg* data incorporate both the information provided by equity market analysts and the testimony of market professionals whose trading decisions ultimately determine prices, the wraps provide direct evidence of the process driving stock prices.

In contrast, traditional econometric analysis, fraught with limitations, forces economists to infer causal processes in equity and other asset markets by regressing prices on some information set. There is, however, little notion in the raw data themselves as to what the causal process is. A main benefit of the *Bloomberg* data is that they embody direct evidence of this process without being hampered by the need to estimate it. Take, for example, the following market wrap story from April 18, 2001.

> U.S. stocks rallied after the Federal Reserve surprised investors by cutting interest rates for the fourth time this year. The Nasdaq Composite Index soared to its fourth biggest gain. [April 18, 2001]

The story paints a clear picture of the process driving stock prices on that day: a cut in interest rates by the Federal Reserve was the main causal factor pushing the stock price upward.

In addition, the textual data allow for measurement of the relative importance of psychological and technical considerations. Such factors are

troublesome to empirical economists due to their inherent elusiveness as they possess a slippery and unquantifiable connotation to them. Indeed, it is not straightforward how one can measure the sentiment of the market. The textual data, hinging on market participant testimony and analyst accounts, however, are able to extract the prominence of such considerations in influencing short-term stock price fluctuations.

The data also allow for measurement of the importance of fundamental considerations without predetermining when and in what way they may matter for stock prices. Indeed, structural change in stock-price relations is a predominant and potentially attenuating issue facing time series econometricians. In contrast to traditional econometric analysis, the *Bloomberg* stories circumvent this matter by not specifying in advance how this relationship may change, leaving open the possibility of it occurring in non-routine ways.

2.2.3 Limitations of the *Bloomberg* Data

No data are perfect and the *Bloomberg* data are no exception. First, the data are based on the sole reading of the market wrap stories by one researcher. A particular story may be read differently by different people, making it unlikely that another reader would replicate the dataset exactly. Take, for instance, an excerpt from the wrap story on May 23, 1995.

> U.S. stocks closed higher amid optimism that a fragile economic
> recovery would dissuade the Federal Reserve from raising interest
> rates any time soon. [May 23, 1995]

One reader of the excerpt may record interest rate cuts from the Federal Reserve as the primary driver of the daily stock price while another may score the economy as the principle factor or both. However, there is not so much ambiguity in the stories: the wraps are fairly clear in reporting on the factors deemed relevant in driving day-to-day stock price movements. Furthermore, although some readers would no doubt score some wraps differently, it is unlikely that the scoring would be so different as to lead to different conclusions about the implications of bubble and IKE models. Given the sheer magnitude of the number of observations (4,206), it seems reasonable that the more salient features of the market wrap stories will be uncovered. But, this conclusion has yet to be examined.

The *Bloomberg* data rely on interviewing equity fund managers and, therefore, may suffer from some of the shortcomings that plague data compiled by surveys more generally. There are many issues endemic to such data, but those potentially problematic for the present study are: selection bias, non-response bias and leading question bias – all of which pertain to the format surrounding the interviews of fund managers.[43] Because I am unaware of the process by which the fund managers are selected for interviews and the specific questions involved, there is simply no way to detect the extent to which these issues may plague the data.

The reporting of the *Bloomberg* journalists may also be a source of limitation for this study. Journalists may not be reporting on what happened in the

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[43] These issues are addressed in more detail in Chapter 3. See Graves (1989), and references therein, for a detailed discussion of the problems surrounding survey data.

markets, but merely rationalizing the stock market's movement on a given day in terms of their own ways of thinking. To be sure, the *Bloomberg* journalists generate the market wrap stories based not only on the information and insight provided by market analysts and fund managers, but on their own knowledge of the causal process driving stock price movements. As such, it is not clear how much influence these different channels have on the construction of the market stories.

On the one hand, in an attempt to square the circle regarding the daily stock price movement, journalists may corroborate the market's outcome with trends in fundamental factors. On the other hand, journalists may be predisposed to reporting on psychological and momentum related factors – think fear, greed and herding – as they are more sensational for readers than, say, reports on commodity prices or interest rate movements.

Because the objective of writing the market wrap stories is to provide analysis behind the day's stock price movement, the inclusion of insight from market participants and equity analysts in every story is advantageous for the present study. However, the degree to which the problems outlined above may skew the textual data presented in this study, again, remains an open question.

2.2.4 Analysis of *Bloomberg* Data as Stand-Alone

The bubble and IKE models have sharply contrasting accounts of the basic factors underpinning short-term stock price movements. This sharpness allows for the usage of the *Bloomberg* data to shed light on which class of

models provides the better account. Even though the analysis of textual data is based on descriptive statistics, it may be seen as stand-alone in investigating the main research question of the thesis. This is because each class of models is being compared against a well-specified alternative: one-another. Within each wrap story, the direct evidence on the factors reported as driving market practitioners' trading decisions – whether fundamental, psychological, or technical – and the causal process governing this relationship will support the implications of one class of models *in favor* of the other.

2.3 Econometric Analysis

2.3.1 Limitations of Econometric Analysis

The econometric analysis conducted in Chapters 4 and 5 investigate the stability of stock-price relations and the question of whether fundamentals matter for price fluctuations, respectively. The process of specifying an empirical model required to carry-out such an analysis is, however, fraught with many limitations.[44] One important problem is that it is not clear what causal process is to be inferred from the raw data. This is a serious issue.

Theory is useful for bridging this gap but only as a rough guide for model specification. REH models, for instance, imply a very particular set of variables matter for stock prices: interest rates and cash flows. But, it is not clear what interest rate or what definition of, say, earnings to use. To address this problem, the econometric analyses conducted in Chapters 4 and 5 use the *Bloomberg* data to help guide the transition from theory to empirical specification. In

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[44] See Phillips (2003) for a discussion on this.

particular, the fundamental factors identified by the *Bloomberg* stories as the most important for market participants are included in the econometric model.

2.3.2 Benefits of Econometric Analysis

Even though econometric analysis has its limitations, it has several benefits over the textual data. First, unlike the *Bloomberg* analysis which may be viewed as inherently "loose", the econometric analysis provides more formal testing of some of the hypotheses of primary importance to the thesis, namely whether and how fundamentals matter for stock prices. The sophistication of the statistical techniques employed in Chapters 4 and 5 allows us to focus specifically on these hypotheses.

Second, unlike the *Bloomberg* data, the econometric analysis is not constrained to examine only the 1990's and 2000's. Indeed, the time period investigated in Chapters 4 and 5 span five decades of data from 1959 through 2009. One could argue that the sample period investigated with the textual data is unique in the sense that two dramatic events unfolded during this period which were unprecedented in post World War II capitalist economies: the long upswings in equity prices in the late 1990's and the Financial Crisis beginning in 2007. As such, it is useful to investigate whether the features which are reported in the market wrap stories as characterizing stock price movements are corroborated in the formal econometric analysis which covers a longer time period.

2.3.3 Econometric Analysis as Stand-Alone

As with the *Bloomberg* analysis of Chapter 3, the econometric analysis conducted in Chapters 4 and 5 stands alone in their conclusions regarding the fundamental relationships in stock markets. Though the formal empirics draw on the *Bloomberg* data for model specification, the inferences drawn from it are independent from those drawn from the *Bloomberg* analysis.

The objective of Chapters 4 and 5 is to test whether and how fundamentals matter for stock price fluctuations. As such, the inclusion of causal factors based on the market wrap stories does not, in any way, slant the empirical analyses of Chapters 4 and 5. Recall that a primary distinction across models is the extent to which fundamental factors matter, if at all, for stock prices. Therefore, using the *Bloomberg* data as a guide in model specification does not sway the empirical results in favor of one approach over another.

2.3.4 Comparing the *Bloomberg* and Econometric Analyses

The *Bloomberg* and econometric analyses employ alternative approaches to investigating the main research question of this thesis. Each has its own limitations and drawbacks. It is thus useful to compare the results of these different approaches. To the extent that these results do or do not point in the same direction would increase or decrease the confidence we may have in the results of the separate analyses.

The identification of changes in the causal process underpinning equity market outcomes is one such analysis that may be compared across empirical approaches. Because the *Bloomberg* analysis has its limitations and there is no objective way to econometrically test for structural change, different analyses will lead to different conclusions about the extent to which temporal instability is present and the locations of potential breakpoints. However, by comparing the *Bloomberg* and econometric analysis of temporal instability, there is the opportunity for the results from both to be given more confidence.

CHAPTER III

FUNDAMENTALS, PSYCHOLOGY AND TECHNICAL CONSIDERATIONS IN EQUITY PRICE MOVEMENTS: EVIDENCE FROM *BLOOMBERG NEWS*

> People...say economics needs to incorporate the insights of psychology. Great. Thanks. I've heard that from (Robert) Shiller for thirty years. Do it! And do it not just in a way that can explain anything. Let's see a measure of the psychological state of the market that could come out wrong. That's hard to do. Calling for where research should go is fun, but I think it is far too easy.
>
> John Cochrane interview
> *The New Yorker*, January 13, 2010

3.1 Introduction

The purpose of this chapter is to confront the competing implications of bubble

and IKE models with empirical evidence. To date, there have been numerous

calibration studies of non-REH models, but, to my knowledge, none that confront

bubble models with time-series data. Indeed, it is not clear how to test the bubble

models' predictions that psychological and technical momentum-related factors

drive short-term stock price movements. Such factors are difficult to measure let

alone incorporate into formal statistical analysis. IKE models too are problematic:

they imply that the fundamental relationships that drive short-term price

movements change at times and in ways that do not conform to any mechanical

rule. It is unclear how to incorporate such temporal instability into formal

empirical analysis.

This chapter deals with these problems by making use of a novel dataset that I constructed for this study.[45] The data come from information contained in *Bloomberg News'* daily "Market Wrap" (end-of-the-day) stories, for the period January 4, 1993 through December 31, 2009.[46] In writing market-wrap stories, *Bloomberg* journalists rely on a revolving cohort of 100-200 equity fund managers and other actors who are directly involved in the markets. As such, these stories provide a window into the decision-making of the professional players, whose trading determines prices.

Unlike the quantitative data typically used by researchers in carrying out formal statistical analysis, the textual data contained in *Bloomberg's* reports are not constrained to track the importance of only fundamental considerations. *Bloomberg* journalists indicate in their reports that psychological considerations, such as confidence, optimism, and fear, as well as technical considerations, such as momentum-trading, profit taking, and the January effect, also play roles in professionals' day-to-day trading decisions. Moreover, my textual data are able to uncover the importance of psychological, technical and fundamental considerations for stock price movements without having to impose any fixed relationship between these factors and prices. By doing so, the *Bloomberg* data enable me to confront the competing implications of bubble and IKE models of asset prices, thereby providing new insights into equity price dynamics.

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[45] Some preliminary findings from my *Bloomberg* dataset are presented in Frydman and Goldberg (2011).

[46] The author gratefully acknowledges *Bloomberg L.P.* for generously providing access to, its subsidiary, *Bloomberg News* and its historical data for this study.

I first present the *Bloomberg* data and discuss their limitations. The data are plagued by some of the shortcomings endemic to survey data. There are also issues regarding the collection of data, the transcription of information by journalists when writing the wraps as well as other issues that may be problematic.

The data, however, do allow me to examine the following questions, which help cast light on which class of models provides the better account of short-term stock price movements: (i) what are the relative roles of fundamental, psychological and technical considerations?: (ii) do different factors matter during different periods?: (iii) do pure psychological and momentum-related considerations sustain persistent upswings?: (iv) do certain fundamental considerations matter more than others?: (v) what are the qualitative relationships between causal factors and stock prices and do these relationships change over time?: and (vi) does the frequency with which causal factors matter change over time?

In general, if the bubble view provides the better account of stock price swings we would expect to see accounts of crowd psychology and technical momentum trading underpinning short-term stock price movements. If, however, IKE models provided the better view, the stories would entail movements in fundamentals driving stock price behavior in addition to an intermediate influence of psychological considerations on the translation of these trends into market participants' price forecasts.

This chapter is organized as follows. Section 2 discusses the methodology and scoring system behind the *Bloomberg* data as well as the data's limitations. Section 3 outlines how I categorize the information contained in the *Bloomberg* stories. Section 4 provides a descriptive analysis of the data and examines which model of stock price fluctuations receives more support. Section 5 concludes.

3.2 *Bloomberg* Data: Methodology

3.2.1 A Novel Dataset

The largest financial news firm by market share and bellwether for information on market behavior is *Bloomberg* L.P. Its subsidiary, *Bloomberg News*, a major news wire service, provides data, software, and analytics for more than 250,000 clients worldwide, including 450 newspaper and magazine outlets.

The textual data come from reading end-of-day equity market wrap stories prepared by *Bloomberg News*. Each day, these stories report the primary factors that participants in the equity market relied on in their trading decisions for that day. In their reporting, *Bloomberg* journalists also indicate the qualitative relationships between each day's relevant factors and the stock price, that is, whether they impacted the stock price positively or negatively. In all, I read 4,206 market-wrap stories over the period January 4, 1993 through December 31, 2009.

By reading the *Bloomberg* stories, I am able to circumvent important limitations plaguing other studies that rely on textual data.[47] The textual data used by these other studies are based mostly on automated word counts. These data are unable to fully discriminate between the variables that really drove the market from ones that did not. This is because tracking the frequency with which certain words are mentioned ignores the context in which they are reported.

Consider, for example, the following excerpt from a *Bloomberg News* report: "Stocks dropped as the Federal Reserve Bank increased the Fed Funds Rate 25 basis points to stem an overheating economy. Last week's reports showed the economy grew 4% from the previous quarter and the Index of Leading Economic Indicators grew 2%." A simple word count of this excerpt would identify the "economy" as a primary factor behind the day's price movement, when in fact, the excerpt singles out only the interest rate as the main driver of the day's stock market.

Beyond the problem of overweighting and underweighting the importance of causal factors, word-count data provide no indication of whether a particular variable mattered positively or negatively for asset prices. As we will see, such information provides important clues about the causal process underpinning stock prices and how this process changes over time.

For the most part, the *Bloomberg* stories are concerned with movements in the overall equity market, rather than particular stocks. They make use of three indices in reporting how "market" prices moved: the Dow Jones Industrial

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[47] Most studies utilizing textual data are based on automated text mining systems and are found in information sciences journals. I provide a detailed review of this literature in the appendix to the chapter.

Average, the Standard and Poor's 500 Composite Index and the NASDAQ Composite Index.[48] Of course, these indices do not move in the same direction every day.[49] However, this is not a problem for my scoring of the information contained in the market-wrap stories. I treat the mention of a particular variable as a main driver of stock prices the same regardless of what stock market price index the story mentions.

3.2.1.1 Limitations of the *Bloomberg* Data in Detail

Although the *Bloomberg* dataset has several strengths – most notably the ability to measure the relative importance of psychological and technical factors for stock prices and allowing for fundamentals to matter in non-routine ways – it also has limitations which have been sketched in Chapter 2. This subsection will focus on two areas of potential shortcomings with the textual data when testing the competing implications of bubble and IKE models: the anecdotal evidence of equity fund managers and the role of journalists.

On a daily frequency, the *Bloomberg* journalists solicit explanations of the market's movement from financial professionals and equity fund managers. Even though 100-200 managers are called upon throughout the seventeen year period, the wraps typically contain the responses of only a few. As such, the testimony of one or two fund managers who are selected on a given day may not

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[48] The reporting of the NASDAQ as driving the "aggregate" U.S. market diminished at the start of 2009. Throughout this year movements in the NASDAQ were reported in the wrap on only 24 out of 238 trading days, or roughly 10% of the time.

[49] Over the entire sample, the three indices mentioned above moved in the same direction on a given day (measured as the difference between closing and opening price) 74% of the time. The Dow and the S&P 500 moved in the same direction 88% of the time.

be representative of the entire population. For the present study, this selection bias may refer to equity fund managers with relatively large amounts of capital at stake. This is a desirable characteristic as fund managers with a greater stake in the market will exert more influence on prices through their trading decisions. As such, their testimony of stock price movements should carry greater consideration in the analysis.

In addition, it is unclear how homogeneous the views are across managers. Non-response bias may occur when those that chose not to respond to the questioning have significantly different views than those who do choose to participate in the survey. For this study, it is difficult to assess the magnitude of this disparity: we simply do not know who was contacted but declined to interview.

Who the journalists are also matters for the quality and consistency of the reporting in the market wraps. Fortunately, there were only approximately 10 journalists for the equity market over the seventeen year period and they collaborated on many of the wraps. It was typical to have at least two journalists involved in a day's report. As mentioned in Chapter 2, along with the insight from market analysts and practitioners, the journalists may also rely on their own understanding and knowledge of the process driving stock price movements. Although we do not have information on the credentials of the journalists, it may be reasonable to presume that those overseeing *Bloomberg's* coverage of the day-to-day movements of stock prices and the structure of equity markets are top-notch in their profession.

3.2.2 *Bloomberg* Data: Scoring

The construction of the *Bloomberg* dataset entails collecting and recording those factors that the wrap stories indicate underpinned price movements in the aggregate market each day. These factors are recording with a +1 or a -1, while all other factors in my spreadsheet are given a zero for the day. The positive or negative sign indicates the qualitative relationship between each factor and the stock market price. A plus (minus) sign denotes a positive (negative) relationship *given the market expectation*.

Consider, for example, the market wrap from July 23, 2004 which reads,

> U.S. stocks dropped after earnings from Microsoft Corp. and sales at Coca-Cola Co. fell short of analysts' estimates...Expectations were very high and the Street is clearly disappointed these companies didn't beat them.

In this case, earnings rose but failed to meet or exceed expectations, thereby driving the market downward. Although the rising earnings were associated with a falling market, it is clear from the story that the relationship between earnings and stock prices is a positive one. I thus scored such reports with a +1 for earnings.[50]

Because *Bloomberg Inc.* is a major hub in constructing and providing survey expectations data based on information from major financial institutions around the world, such data are often included in the report as representing the "market's" expectation.

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[50] A detailed description of this scoring methodology is provided in the appendix to this chapter.

Expectations of future events also play an important role in the scoring of the wrap stories. The following excerpt provides an example of this scenario.

> U.S. stocks slumped on concern that companies like Cooper Tire and Rubber Co. and Apple Computer Corp. will report lower than expected earnings. [June 8, 1993]

If the expectation of an outcome yet to occur – in this case earnings reports – is reported as driving the day's stock price movement then it is recorded with a (+) or (–) 1 given the implied directional relationship with the stock price. This may lead to potential over-reporting and thus over-recording of these factors as the expected event or outcome may not come to fruition.

To be sure, it is not clear how large of a problem this is for the purpose of this study. For instance, the anticipation of a movement in a fundamental factor, say, the expected outcome of a GDP report, may be just as likely to be reported on as driving the stock price as the expectation of the outcome from a technical consideration, say, Triple Witching Friday.

3.3 *Bloomberg* Data: Factor Categorization

3.3.1 Fundamental Considerations

Over the seventeen years of my sample, the *Bloomberg* journalists identified a great many factors that drove the stock market. I placed these factors into one of three categories: psychological, technical trading and fundamental. Any non-psychological or non-technical factor that market participants looked to in forming their forecasts of market outcomes is treated as a market fundamental. Three

excerpts illustrate how the importance of these fundamental factors was reported.

> US stocks rose, sending the Dow Jones Industrial Average to its first gain in six days, after General Electric Co., the second-biggest U.S. company by market value, said 1999 earnings will meet expectations. [December 15, 1998]

> US stocks rallied after the Federal Reserve surprised investors by cutting interest rates for the fourth time this year. The Nasdaq Composite Index soared to its fourth biggest gain. [April 18, 2001]

> "The environment is pretty doggone good for stocks," said Robert Phillip, chairman of Walnut Asset Management LLC, which oversees $725 million in Philadelphia. "Earnings appear to be stronger than anticipated." [March 1, 2004]

Table 3.1 presents the range of disaggregated factors that enter the fundamentals category. In total, there are 89 disaggregated fundamental factors that were reported in the wrap stories.[51] In order to facilitate the descriptive analysis presented later in the chapter, I grouped the fundamental factors into seventeen categories: the Economy, Interest Rates, Oil Prices, Inflation, Currency Markets, Earnings, Housing, Sales, Gap/Valuation, Trade, Company Variables, U.S. Government, U.S. Central Bank, Consumption, Terrorism, U.S. Financial/Credit Market, and Rest of World. These categories are also provided in Table 3.1. For the most part, the fundamental categories that I selected are fairly straightforward. For example, the economy category includes mentions of GDP, industrial production, employment and manufacturing, which are all indicators of the health of the overall economy.

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[51] This number is based on cataloguing the Rest of World (ROW) as one factor. This factor includes any fundamental factor that was mentioned if it pertains to a foreign country. For instance, if interest rate cuts in the European Union impacted the U.S. equity markets it would fall under the ROW category.

However, I had to make some decisions in constructing the fundamental categories. Notice from Table 3.1 that earnings or profits and sales or revenue are not included in Company Variables. As we will see below, company earnings were mentioned quite frequently and as such, were given their own category. On the other hand, it was difficult to distinguish between a company's sales or revenue and reports of auto sales or retail sales. As such, I created a separate category for company sales or revenue. Also notice, there are no two categories with the same fundamental factor except for the Fed Funds Rate and Monetary Policy – which is merely a different name for the same factor – and "bailout" which is included under Central Bank and Government. This double entry captures the source of the rescue funds.

The Gap/Valuation category also deserves some discussion. As I discussed in Chapter 1, the IKE model implies that the divergence between current prices and perceptions of historical benchmark values is important in how individuals' assess risk and forecast future prices. The *Bloomberg* Wrap stories provide some evidence corroborating this view. Three excerpts below illustrate this consideration:

> U.S. stocks fell in a late-day slide amid concern that share prices may have overshot earnings prospects..."There are an increasing number of people who think this market is overvalued," said David Diamond, a money manager at Boston Company Asset Management with $17 billion in assets. The Standard and Poor's 500 Index is trading at 19 times 1997 earnings, based on a Zacks Investment research survey, 25% higher than its average price-to-earnings ratio of 15.2 since 1980. [February 19, 1997]

"Investors are looking for a reason to sell," said Gene Grandone, director of investment counseling at the Northern trust Co., which oversees $130 billion. "With the market in the 7,900 area, people see a market that is a little rich."...Many investors are uncomfortable with the market's price-to-earnings ratio, which is near the high end of its historic range. [July 7, 1997]

U.S. stocks were mixed...Companies are being punished for any shortfalls because stocks are at historic highs relative to profit forecasts. The S&P 500, for example, trades at 35 times earnings. [April 7, 1999]

As these excerpts illustrate, the gap considerations deal with deviations of current prices from estimates of historical benchmark levels. On the other hand, valuation factors are more concerned with prices relative to some measure of the economy such as earnings or dividends. The excerpt from February 14, 1998 reads, "Stocks fell as investors are concerned about valuations...Many stocks are priced higher than justified by the outlook for corporate profits." Because valuations were not mentioned relative to a benchmark level, they are not considered to pertain to the gap.

3.3.2 Psychological Considerations

In scoring mentions of the psychological factors reported in the *Bloomberg* wraps, I relied on the large behavioral finance literature. Hirshliefer (2001), Barberis and Thaler (2002) and Shiller (2005) suggest that the following psychological factors may be important: optimism, pessimism, confidence, sentiment, greed, fear, concern, worry, exuberance, mania, panic, crowd

psychology and euphoria. The following two excerpts illustrate how *Bloomberg's* journalists reported on the impact of pure psychological considerations.[52]

> "I do think it's mania," said Ned Riley, chief investment officer at BankBoston Corp., which oversees $26 billion. "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." [April 21, 1998]

> "The selling is feeding on itself," said Ned Riley, chief investment officer at BankBoston Corp., which oversees $30 billion. "People are indifferent about stock prices and valuations. Now they're fearful." [August 4, 1998]

Table 3.2 lists the psychological factors that are reported on by *Bloomberg* journalists. Like the fundamental considerations, I had to make some decisions regarding the scoring of psychological factors. For example, the psychological considerations "concern" and "worry" were included because they constitute an altered state of emotion that may impact market participants forecasting, much like the more traditional psychological factors "fear" or "optimism".

Another issue I faced in cataloguing these factors was the reporting of The Consumer Confidence Index and the University of Michigan Consumer Sentiment Index. Though both include the psychological factors of market "confidence" and "sentiment", these indices are based on household consumption patterns and forecasts of future economic conditions, respectively. As such, they do not constitute as pure psychological considerations.

This leads to the close connection that *Bloomberg* journalists reported on between psychological factors and fundamental considerations. Two of *Bloomberg's* wrap stories illustrate this close connection.

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[52] Pure psychological considerations refer to those mentions of psychological factors that are independent of any other consideration as driving stock price movements.

"IBM earnings are extremely positive," said Howard Cornblue, a money manager for Pilgrim Investments, which oversees $7 billion. "This will give confidence and stability to the market." [April 21, 2009]

"You have got a lot of fear going into earnings," said John Nichol who manages $1 billion in Pittsburgh including the Federated Equity Income Fund, which has beaten 74 percent of its peers over the past five years. [March 2, 2009]

3.3.3 Technical and Momentum-Related Considerations

The technical considerations reported on by *Bloomberg* journalists are catalogued in Table 3.3. These factors are grouped into two distinct subcategories: technical momentum and technical non-momentum. The former includes mentions of participants extrapolating past price trends because they relied on technical trend-following rules (often called "chartism") or some other feedback strategy that leads to so-called "momentum" trading. Three excerpts from *Bloomberg's* market-wraps illustrate how these factors are reported:

International Business machines Corp. led the Dow average's drop after falling below its 50-day moving average....accounting for all of the Dow average's decline. [August 2, 1999]

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. [January 11, 2001]

"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," Rittenhouse's Waterman said. [October 4, 2001]

The other subcategory of technical considerations entails factors that are not likely to be triggered by past price trends or chart-watching. Such factors include profit taking, a firm being added to an index, triple witching, and

numerous effects such as the January, Monday and Friday effects.[53] Two

excerpts from *Bloomberg's* wrap stories illustrate these factors:

> "U.S. stocks closed broadly lower after a sell-off triggered by today's
> quarterly expiration of stock options and stock-index options and futures
> sent the market reeling in the final hour." [6/18/93]

> U.S. stocks declined today, breaking a string of record highs in 1994, as
> investors cashed in gains before tomorrow's crucial report on wholesale
> prices. "It's a predictable backlash," said Jim Benning, a trader at BT
> Brokerage. "We were up so much in the past few days." [1/11/94]

3.4 Results

3.4.1 Overall Importance of Fundamental, Psychological and Technical Considerations

Table 3.4 presents a descriptive analysis based on the textual data collection and

categorization methodology as described above. The factors that have been

outlined in Tables 3.1, 3.2 and 3.3 are listed in the first column of Table 3.4. The

second column displays the average factor frequency of each factor defined as

the total number of days over the entire sample that said factor was mentioned

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[53] Profit taking entails the decision to reduce or eliminate a profitable position in order to realize some or all of its gains. The Monday effect refers to the tendency of stock returns to be lower on Mondays than on other days. The firm addition effect occurs when a firm is added to an index typically having a positive effect on index prices (though this may be purely due to the reallocation of index portfolios where managers attempt to capture a consistent weighting of all stocks). The Holiday, Santa Claus, or end-of-the-year effect refers to the tendency for stocks to increase during the week in-between Christmas and New Year's. This is conjectured to occur for tax considerations, happiness around Wall Street, people investing their Christmas bonuses, and the anticipation of higher returns usually experienced in January. The January effect refers to the tendency for stocks (small-cap) to realize positive returns in this calendar month. The end-of-month and quarter effects refer to the tendency for returns to be higher towards the end of these periods as fund managers unload cash and purchase stocks (usually year-long winners) attempting to boost portfolio values before reporting season. The Friday effect refers to the apprehension of market participants to hold open positions over the weekend exerting downward pressure on the market price at the end of the week. The Monday effect refers to the finding that Monday returns are too low to compensate investors for holding open positions over a weekend of uncertainty. Triple witching refers to the simultaneous expiration of stock index futures, stock index options and stock options on the same day. This happens four times a year on the third Friday of March, June, September and December. The giving back effect refers to the notion that past short term movements in stock prices have been excessive and therefore the market must "give back" in response.

as underpinning stock market movements divided by the total number of trading days for the period. The third column reports the sign of the directional relationship that each factor shares with the aggregate market price given expectations and the frequency with which this relation held over the sample period.

Table 3.4 shows that a wide array of fundamental factors underpin individuals trading decisions. As implied by IKE models, fundamental considerations are unambiguously reported as the primary driver of short-term stock price fluctuations. The second column reports that fundamental factors are mentioned as underpinning short-term stock price movements virtually *every* day over the seventeen year period, or 99% of the days.[54] Not surprisingly, earnings merited the most attention (65%) followed by the economy (47%) and interest rates (38%).[55]

As also implied by IKE models, psychological considerations are found to play a substantial role in contributing to shorter-term price fluctuations. Such factors were deemed relevant 55% of the time. However, on nearly every occasion (54%) psychological considerations were tethered to a fundamental factor (See Section 3.3.2). Consequently, the bubble models' implications that pure psychological considerations drive short-term price movements received support only 1% of the time, or roughly two and a half days per year. Moreover,

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[54] That is, on 99% of the trading days at least one of the disaggregated fundamental factors was deemed relevant in the aggregate market outcome for the day.

[55] For earnings (the economy) the above frequency measure of 65%(47%) captures both direct as well as the indirect effects for profit (economy). The following wrap illustrates this: "U.S. stocks rose as declining interest rates boosted the profit outlook for J.P. Morgan & Co. and other banks." [July 1, 1997]. A direct linkage of earnings (economic) reports reveals a frequency of 40%(35%) over the sample period.

the bubble model's implication that technical momentum-related considerations drive the market, also receives very little support, mattering 5% of the time, or one day per 20-day month.

The bubble view that psychological considerations drive short-term market movements and alone are enough to sustain long upswings in stock prices is difficult to reconcile with trends in fundamentals. The finding that psychological factors are almost always connected to a fundamental suggests that much of the emotion underpinning the upswings of the late 1990's and 2003 through 2007 period and subsequent sharp reversals was infused by trends in such causal factors as company earnings and overall economic activity. Any confidence and optimism that might exist in the market would quickly evaporate if, say, earnings and overall economic activity consistently moved in the opposite direction.

In general, the overall factor frequencies based on the *Bloomberg* data provide support for the IKE model's implication that fundamental factors are the primary driver of short-term stock price movements. Also consistent with the IKE view, psychological considerations were found to be quite important in helping market participants translate movements in fundamentals into their forecasts of future prices. The bubble view that pure psychological and momentum-related considerations underpin stock market behavior received virtually no support in the *Bloomberg* market wraps.

However, tracking the overall factor frequency may be masking the importance of the bubble view. Indeed, we might expect the influences of pure psychology and technical trading to only be important during long upswings in

stock prices. To give the bubble view the benefit of the doubt, I investigate monthly factor frequencies over the entire sample.

3.4.2 Uncovering Change in Factor Frequencies

Calculating an average impact of any causal factor over the *Bloomberg* data's seventeen year period can mask behavior from month to month or year to year. To address this problem, I derive the factor frequency each month by taking the number of days a factor was reported as relevant by market participants and dividing by the total number of trading days in each month. However, generating a factor frequency over monthly horizons introduces a high degree of volatility in the time series from month to month. To address this problem, I calculate a 12-month trailing average to smooth the series. This new factor frequency is the one plotted in most of the figures presented in subsequent sections.

These "factor frequencies" do not reflect parameter weights or coefficients. Indeed, a factor such as interest rate hikes by the Central Bank may have profound impacts on the market even though its occurrence is rather infrequent. To be sure, some factors are simply mentioned less frequently than others because their data is only released at lower frequencies – inflation, consumer, GDP and trade data come to mind. The monthly factor frequency merely reflects the average magnitude of occurrence per month with which any factor is reported as a major contributor to daily stock market movements. A factor's importance for stock price movements may be assessed from this measure but, when factor

frequencies rise or fall, it is not clear whether the causal factor's impact on prices is changing.

3.4.2.1 Psychological Considerations and the Bubble View

Table 3.4 shows that psychological factors are found to merit a great deal of attention by market participants. The factor frequency for the overall influence of psychology on the market is illustrated in Figure 3.1. The aggregate influence of psychological considerations dropped sharply through the year 1996, precisely the period imputed with "irrational exuberance" by proponents of the bubble view. However, consistent with the IKE account, the influence of several fundamental factors, such as earnings, was quite strong through the late 1990's (discussed below). Still, proponents of the bubble view contend that the upswing in asset prices during the late 1990's and 2003 through 2007 periods resulted from elevated influences of pure psychological factors on the trading decisions of market participants. Indeed, many argue that psychological factors exert their greatest influence on the market at the peaks of price swings. Figure 3.2 illustrates the monthly factor frequency of the influence of pure psychological considerations on the aggregate market.

The striking feature of this graph is that pure psychology alone plays a very limited role in driving short-term stock price behavior and thus long swings, reaching a pinnacle of 4%, or less than 1 day per month in December 1999, a full 8 months before the upswings in equity markets reached their heights.[56] To be sure, the influence of pure psychology is elevated during the upswing of the

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[56] The S&P 500 peaked in August 2000, reaching a value of 1485.

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1990's, possibly providing limited support for the bubble view, but with a maximum impact of 4%, it is difficult to argue such factors alone can consistently underpin shorter-term price fluctuations and sustain long upswings in stock prices.

In addition, the upswing in housing, equity, and other asset prices reaching its height in October 2007, does not corresponded to any increase in the influence of pure psychology based on the *Bloomberg* market wraps. This consideration averaged a factor frequency of roughly 0.5% from 2004-2008. Technical momentum and non-momentum related factors tell a similar story in Figures 3.3 and 3.4, respectively.

To be sure, the most conservative measure of the bubble view would include a confluence of crowd psychology and technical momentum-related considerations that underpin asset price swings (see Chapter 1). In providing the most comprehensive, and conservative, interpretation of the bubble view, in addition to the factors consistent with pure psychology, technical momentum related effects are included. These results are illustrated in Figure 3.5.

At its peak, factors corresponding to the broadest measure of the bubble view, merit attention less than 10% of the time – or approximately two days per month. Moreover, the peak of bubble considerations occurred in February 1999, a year prior to the peak in stock prices and valuation ratios. And, similar to the influence of pure psychology, there is almost no increase on 2004-08 to correspond to the upswing in equity and housing prices which preceded the

Financial Crisis. Overall, the evidence provides very limited support in favor of the bubble view of price swings in equity markets.

3.4.2.2 Change in Factor Frequencies of Fundamentals: The IKE View

As implied by IKE models and supported by the *Bloomberg* data, market participants pay attention to a wide range of fundamental factors in formulating trading decisions. But, the results also show that the composition of fundamentals was not fixed over the period. Figure 3.6 shows that the monthly average of the number of disaggregated fundamental factors that individuals deemed relevant in trading decisions was highly variable. For instance, from 2000 through 2001 the average number was three while from 2006 through 2007 it was closer to five.[57] Looking at the variation in monthly factor frequencies for single fundamentals tells a similar story consistent with the IKE view of asset markets.

Even though earnings merited the most attention by market participants over the period, its relationship with the stock market price was not fixed over time. The factor frequency of earnings plotted in Figure 3.7 shows that the influence of earnings on the market fluctuated between a range of 50% to 80% over the seventeen year period. Though the importance of earnings is highly variable, such variation is even more pronounced for other fundamental factors.

Figures 3.8, 3.9 and 3.10 graph the monthly factor frequencies for oil prices, interest rates and inflation, respectively. The graph for oil prices is,

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[57] *When* individuals may pay attention to certain variables over others is difficult to know in advance (see Chapter 6).

perhaps, the most striking. Up until 2004, market participants paid little attention to oil prices, meriting attention roughly 5% of the time. However, in the beginning of 2004 the proportion of days for which oil prices mattered skyrocketed to 60%, remaining at elevated levels throughout the duration of the period. Similarly, the inflation rate mattered 45% of the time by the end of 2006 only to drop to 5% not two years later.

This overwhelming evidence across fundamental factors suggests that, given the variation in the timing and magnitude for which certain fundamentals merit the attention of market participants in underpinning their stock price forecasts, it would be difficult to adequately capture such change with a single overarching mechanical rule.

3.4.2.3 The Gap Effect

The seemingly inherent pattern of high degrees of variation in monthly factor frequencies in the *Bloomberg* data is also illustrated in the gap effect implied by IKE models (see Section 3.3.1). Figure 3.11 suggests individuals paid little attention to the departure of stock market prices from estimates of common benchmarks levels, mattering less than 2% of the time, from 1993 through the end of 1996. However, this measure increased to over 10%, peaking in October of 1999. This elevated factor frequency preceded by two months the unprecedented S&P 500 price-to-earnings peak of 44.2 in December 1999. The importance of the gap measure experienced a similar rise at the end of 2008

when market valuations were, most likely, considered to be low, even compared to century-long historical benchmark levels.[58]

To be sure, it is hard to judge what causes the frequency with which a fundamental factor is deemed relevant to undergo dramatic fluctuations as those observed in oil prices, interest rates and inflation. The variation in frequency may result from the actual fundamental factor undergoing dramatic change. For example, crude oil prices underwent significant change during 2004, which is about the time that oil prices merited increased attention by market participants.

A second reason for the fluctuations in factor frequency is that the actual fundamentals may be departing from levels consistent with historical averages. For instance, short-term Treasuries were relatively high in the second half of the 1990's and from 2006-2007, approximately the same subperiods when interest rates received greater attention by market participants. This issue is investigated further in Chapter 6.

3.4.3 Identifying Points of "Change"

The last column in Table 3.4 reports the directional relationship that the aggregated fundamentals shared with the stock market price over the seventeen year period. Unsurprisingly, earnings had a positive impact on the stock market price 100% of the time, while inflation and interest rates both shared a negative relation 98% of the time. For stock markets there is little to guide the directional relationship of movements in some fundamentals on prices.

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[58] The price-to-earnings ratio for the S&P 500 was roughly 15.25 in November 2008; below the historical average of 15.6 dating back to the late 19th century.

Consider a rise in overall economic activity, say, in the form of increased industrial production. Conventional textbook theory predicts that individuals may revise upward their expectations of future earnings or dividend streams exerting upward pressure on stock prices. However, periods of economic expansion are also associated with increases in prices, monetary tightening and thus higher interest rates, which are used to discount future earnings and dividend streams, exerting downward pressure on stock market prices.[59]

IKE models imply that much of the change that underpins fundamental relations in asset markets does not conform to any mechanical rule. The *Bloomberg* reports find that several fundamental considerations do not possess the directional uniformity with the stock market price as that observed with earnings, interest rates and inflation. For example, the economy mattered positively 60% of the time while oil prices mattered negatively 54% of the time.

As implied by IKE models, variation in the qualitative relationship a fundamental factor shares with the market is suggestive of change in the way that individuals interpret trends in fundamental considerations when formulating forecasts of market outcomes. Thus, in identifying periods of "change" in the way individuals think about the future, shifts in qualitative relationships are a conservative measure of such change.

Figures 3.12 and 3.13 illustrate the variation in the directional relationship between the economy and oil prices and the stock market price. For both series, periods are identified where the directional relationship crosses the 50%

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[59] For instance Boyd *et al.* (2005) show that stock market prices react differently to news on unemployment during expansionary and contractionary phases in the overall economy. For similar results see Anderson *et al.* (2007).

threshold and maintains its new directional relation with the stock price. For the economy, the proportion of days which it mattered positively as a fraction of its total factor frequency is plotted in Figure 3.12. The economy mattered positively more than half the time from 1993:01 to 1994:05, negatively from 1994:06 to 2000:09 and positively again from 2000:10 to the end of the sample in 2009:12.

For the oil price, the proportion of days which it mattered negatively as a fraction of its total factor frequency is plotted in Figure 3.13. Oil prices mattered negatively more than half of the time from 1993:01 to 1994:11, positively from 1994:12 until 2002:11, negatively again from 2002:12 to 2007:06 and positively again throughout the rest of the period.

The combined results from the economy and oil price sign changes are plotted against the S&P500 Composite Index price in Figure 3.14. The identified points of change are synchronized with major reversals in stock market price swings. The variation in direction relationship for the economy an oil prices in 1994 correspond to the commencing ascent of the S&P500 Composite Index price. The breakpoint for the economy in September 2000 aligns with the sharp reversal in stock prices following the run-up of the late 1990's. The change in relationship of oil prices and the stock market in November 2002 marks the bottom of the market and the reversal in equity prices which lasted until the second half of 2007 – aligning with another shift in oil price relations.

3.5 Conclusion

The main conclusion to be drawn from this chapter on the basis of the *Bloomberg* stories is that the IKE implication that fundamental factors are the primary drivers of short-term stock price movements, and thus longer-term price swings, is given strong support by the findings. Also consistent with the IKE view, the variation with which certain fundamental considerations merited market participants' attention in forecasting suggests that different fundamentals matter during different periods. This view is strengthened by the shifts in directional relations found for several variables. Psychological considerations were also shown to play a key role in market participants' forecasting behavior, but consistent with the predictions of IKE models, they were almost always tethered to fundamental factors.

The bubble view that psychological considerations alone can sustain stock price swings received almost no support. The broader bubble view including technical momentum-related considerations was found to matter very little and not correspond to peaks of stock price swings. Some may argue that the repudiation of the bubble account on the basis of the *Bloomberg* data is inherently "loose". To this end, Chapters 4 and 5 provide a more formal econometric analysis of the competing bubble and IKE models.

Appendix

A3.1: Textual Data Literature Review

Textual data, unlike quantitative data, relies on information contained in compositional, or text, format. In collecting textual data, researchers commonly follow a hybrid model invoking a text mining learning program in concert with a linear regression of past prices. Due to the challenges associated with staggering amounts of financial news and differentiating relevant information from otherwise, financial studies incorporating textual data are comparatively rare and routinely published in information science journals, largely ignored by mainstream finance and economic publications.

Several text mining systems have been developed aimed at predicting high frequency movements in financial markets.[60] The processes followed in conducting text mining analysis share common threads. The sources of textual information encompass company and independently produced sources. Annual and quarterly company reports fall into the former while analyst reports, financial discussion boards, and news wire feeds pertain to the latter.[61]

The typical procedure to follow in conventional financial research incorporating textual data is two-pronged.[62] First, conducting analysis based on

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[60] See Mitternayer and Knolmayer (2006) for a survey of extant text mining systems incorporating financial news.

[61] The majority of studies employ news wire services due to the frequency of disseminated information and the accompanying objectivity (Wulrich *et al.*, 1998; Lavrenko *et al.*, 2000; Gidofalvi *et al.*, 2001; and Fung *et al.*, 2002). Thomas and Sycara (2000) utilize information contained in financial chat-room postings.

[62] It is important to keep in mind that the vast majority of studies following this approach do so with the objective to forecast high frequency short term price movements in somewhat of a "technical" trading sense.

automated text categorization (as most approaches do) requires the system to be predisposed to a Naïve Bayesian learning phase. This step entails (i) collecting past news articles from, say, the two months prior to the beginning of the actual sampling, or prediction period, (ii) classifying past price movements corresponding to the articles, typically in a qualitative fashion, i.e. "up" or "down",[63] (iii) executing a textual representation scheme, i.e. bag of words (Lavrenko et al., 2000; Schmill et al., 2000; Gidofalvi, 2001) or noun phrases (Tolle and Chen, 2000), and (iv) constructing the learning algorithm by which the system will base future predictions. Since the forecast period is relatively short (most studies entertaining periods of just several months), the training period that the learning algorithm is predicated on is also short in duration.

In the textual representation stage, keywords or phrases may be automatically or manually generated. The former evaluates the words of phrases that are mentioned with the highest frequency in the sampling reports while the latter are commonly provided by market professionals who deem them the most relevant.[64] Whether placing greater weight on keywords or searching for word-tuplets that have the highest frequency of occurrence, both classification approaches suffer from predetermining the information set that market participants deem relevant. Furthermore, the aim of many studies is to "match" current situations with past periods that share common features. For instance,

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[63] An exception is Shumaker and Chen (2010) who assesses the forecasting ability based on discrete stock price movements.

[64] Though few studies incorporate the latter method, Thomas and Sycara (2000), Peramunetilleke and Wong (2001) and Seo et al. (2004) are exceptions.

Peramunetilleke and Wong (2001, p. 131) provide the following rationale for employing this approach.

> "Then knowing how markets behaved in the past in different situations, people will implicitly match the current situation with those situations in the past that are most similar to the current one. The expectation is then that the market now will behave as it did in the past when circumstances were similar. Our approach is automating this process."

This approach suggests that market outcomes unfold from the past in a mechanical way – suggesting that profit seeking individuals adhere endlessly to the same forecasting strategy, never devising novel ways to think about the future. Though numerous counter-examples abound consider the following. If positive GDP growth was mentioned in high frequency during the learning phase, and the market went up, following this approach may miss the alternative effects that an increasing economy have on stock prices. In particular, investors may ignore the possibility that a rapidly growing economy exerts downward forces on the stock market through future tightening of monetary policy and the subsequent decrease in the present value of assets through the effect of increased discount rates.

The second step of the operational phase takes the learning algorithm developed from historical news articles and applies it to contemporaneous news releases; in some cases actual long or short positions are taken based on fixed trading decisions. In order to determine the news articles used in forecasting, a window must be selected. Some studies use overnight articles to predict the following day's closing stock price (Wuthrich *et al.*, 1998). Other's use up-to-the-minute information from news wire feeds such as *Yahoo! Finance* to forecast at

much higher intraday frequencies (Lavrenko *et al.* 2000; Gidofalvi *et al.*, 2001; Peramunetilleke and Wong, 2001; Mittermayer and Knolmayer, 2006). Higher frequency textual data suffers from the potential redundancy or duplicate reporting of the same or very similar events. It is not implausible to conceive that several news wire feeds such as *Reuters* and *PRNewsWire* are picking up on the same up to the minute news.

Even though numerous studies concentrate on very high frequency stock price prediction, several choose end of the day closing prices as the forecast target (Wuthrich *et al.*, 1998; Thomas and Sycara, 2000; Seo *et al.*, 2004). Entertaining such a relatively large lag limits the degree of market responsiveness to news and ignores potential price-relevant information to be revealed in the intermission. However, the difference from when the forecast is made to the realization price does not appear to substantially alter predictability.

Impressively, most studies applying textual data to price prediction report profitable results. In fact, of the six text mining systems surveyed in Mittermayer and Knolmayer (2006) that aim to predict asset price trends, four report positive profit per trading session (Wuthrish *et al.*, 1998; Lavrenko *et al.*, 2000; Gidofalvi *et al.*, 2001; and Mittermayer and Knolmayer, 2006) while four prototypes beat a random forecasting model (Wuthrich *et al.,* 1998; Gidofalvi *et al.*, 2001; Peramunetilleke and Wong, 2001; and Mittermayer and Knolmayer, 2006). However, such promising results should be taken in light of the dismissal of transactions costs and borrowing constraints in many of the trading simulations.

Although the details of each approach outlined above may differ dramatically they share the following features; (i) reliance on a predetermined set of relevant causal factors, automatically or manually chosen, (ii) reliance on programmed text retrieval systems, (iii) unchanging causal environment, i.e. when factors that are selected in the learning phase are associated with a price movement in one direction that relation is expected to maintain during the operational phase and (iv) the aim is short term, mostly intraday, prediction ignoring any longer term influences that can be picked up over longer sample ranges.[65] The present study jettison's all four of the aforementioned characteristics and to my knowledge is the only study incorporating textual data to do so.[66]

A3.2: *Bloomberg* Data: Scoring Methodology

Denote the causal factor X and the stock market price P.

A (+1) is recorded for any for the following five relationships:

- X INCREASES (DECREASES) and P INCREASES (DECREASES); a strict positive relation, OR

- X INCREASES by more than expected and P INCREASES

- X DECREASES by more than expected and P DECREASES

- X INCREASES but by less than expected and P DECREASES

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[65] The vast majority of studies cited above span periods of weeks to a couple months at most.

[66] Schumaker *et al.* (2011) incorporate sentiment analysis into textual data analysis. The authors find that articles involving subjective connotations have marginally greater predictive power than those embodying a more objective tone (negative sentiment is followed by price decreases and vice versa).

- X DECREASES but by less than expected and P INCREASES

A (-1) is recorded for any of the following five relationships:

- X INCREASES (DECREASES) and P DECREASES (INCREASES); a strict negative relation, OR
- X INCREASES by more than expected and P DECREASES
- X DECREASES by more than expected and P INCREASES
- X INCREASES but by less than expected and P INCREASES
- X DECREASES but by less than expected and P DECREASES

CHAPTER IV

BLOOMBERG STORIES AND ECONOMETRIC ANALYSIS OF STABILITYOF STOCK-PRICE RELATIONS

4.1 Introduction

In the previous chapter, the implications of bubble and IKE models were confronted with empirical evidence from *Bloomberg* stories. The analysis pointed quite decidedly in favor of the IKE model and a fundamentals-based explanation of short-term stock price movements. Indeed, there was very little support for the bubble view that pure psychological considerations and momentum trading drive the market, even during the largest upswings and downswings. Moreover, IKE's premise that the process driving stock prices changes at times and in ways that do not conform to any overarching mechanical rule was also given support.

These results, however, are based on a new dataset that has limitations in its ability to pick up the relative importance of fundamental, psychological and technical considerations, as well as whether and how the causal process undergoes temporal instability.[67] Moreover, the analysis of the *Bloomberg* data was necessarily loose; it involved descriptive statistics rather than formal econometric testing of hypotheses. Readers may therefore view Chapter 3's empirical evidence as too informal to serve as a basis for rejecting the bubble class of models in favor of the IKE model.

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[67] These limitations are discussed in Chapters 2 and 3.

The purpose of this chapter and the next is to provide more formal econometric evidence of the importance of fundamental factors in driving short-term stock prices and the temporal instability of this relationship. Of course, econometric analysis is not without limitations. The conditions under which valid statistical inference can be made are difficult to satisfy in most datasets.[68] One of the contributions of this thesis is that it provides analyses based on textual data *and* econometrics. This allows me to examine whether both types of analyses lead to the same conclusions about the importance of fundamentals and the nature and prevalence of temporal instability. A finding that they do would strengthen the conclusions of both.

Estimating fundamental relationships in data that are characterized by structural change is far from straightforward.[69] If I was to model the change with a mechanical rule (for example, with the Marchov-switching model of Hamilton, 1988), I could allow for instability and estimate fundamental relationships in one go. However, in this thesis, I employ a procedure that prespecifies neither the timing nor the nature of instability in the data.[70] I first test a fundamental model of monthly stock prices for temporal instability using recursive techniques that leave open when and how this change takes place. I then use regression analysis to

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[68] Typically, empirical researchers simply maintain these conditions (for example, assuming time invariant relationships) rather than testing whether they are valid. Juselius and Franchi (2006) and Juselius (2007) call this practice "torturing the data."

[69] Autoregressive estimations of most macroeconomic and financial time series data themselves are shown to exhibit parameter instability (Stock and Watson, 1996).

[70] Formal econometric evidence on whether an overarching mechanical rule, like the Marchov-switching model, would provide an adequate representation of the instability in the data is left for future research.

look within the implied subperiods of statistical parameter constancy for evidence on whether fundamentals matter for stock prices.

This chapter discusses the structural change analysis and presents its results, while chapter 5 looks at the question of the importance of fundamentals for stock price movements. The analysis uses monthly data on stock prices and fundamentals and the sample period runs from January 1959 through June 2009.

Remarkably, given the importance of the Lucas critique in macroeconomics, the vast majority of empirical studies investigating the determinants of stock price behavior ignore the problem of structural change altogether;[71] researchers look only for fixed-parameter relationships in the data. There is, however, a growing body of evidence that fundamental stock-price relations are temporally unstable.[72]

The study of Paye and Timmerman (2006) uses the Bai and Perron (1998) sequential SupF test to test for multiple structural breaks in multivariate regressions of the equity premium on the price-dividend ratio, short-term interest rates, default spread and the term premium over a sample running from 1952 through 2003. The authors find evidence of pervasive instability by looking at various combinations of multivariate regressions. In fact, the years of seven of the breaks found in their study match results from this chapter.

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[71] The Lucas critique was aimed at discrediting the premise that analysis of policy changes can be conducted with a single modeling structure which assumes constant parameter weights before and after policy enactment. Because changes in policy would alter the forecasting strategies of individuals, this would also change the causal mechanism. To address this issue, Lucas prescribed REH as a mechanical rule that captures such change. However, we would expect change not only to be non-routine, but to arise for more reasons than just policy changes. See Frydman and Goldberg (2011) for details.

[72] See, for example, Nasseh and Strauss (2004), Paye and Timmerman (2006) and Pettenuzzo and Timmerman (2010).

A recent study by Pettenuzzo and Timmerman (2010) also tests for structural breaks in regressions of the equity premium on the price-dividend ratio and short-term interest rates. Their study examines the posterior probabilities that the moment functions of these variables are generated from different distributions one period to the next over a sample running from 1926 through 2005. Their study finds the price-dividend ratio and short rates have a posterior odds ratio equal to one for eight breakpoints and five breaks respectively. Of the years in which breaks are found, four out of six correspond with results from the current chapter. As such, the results of my analysis add to the evidence of temporal instability in stock-price relations.

One of the novelties of this chapter and the next is that they rely on my *Bloomberg* data in carrying out more formal econometric analysis. REH models imply a specific set of fundamental factors that market participants should use in forecasting market outcomes. However, Frydman and Goldberg's (2007, 2012) IKE model does not: fundamentals matter, but which ones and during which time periods is not specified in the model. It is unclear, therefore, which fundamentals should be included in the empirical model.

However, the *Bloomberg* data give us a good guide as to which variables market participants tend to focus on in forecasting outcomes. Recall that over the entire sample period studied, *Bloomberg* journalists identified 89 different fundamental factors that were important in driving daily stock prices. Even though my sample period involves almost five decades of experience, it would be impossible to include all of these variables in an econometric analysis. Moreover,

data on many of the variables identified by *Bloomberg News* simply do not exist, such as company malpractice, accounting or legal issues, Central Bank comments, political instability, terrorism or financial market regulation.

As such, I include in my empirical model those variables that *Bloomberg* journalists identified as the most important drivers of stock prices (based on factor frequencies) and for which data exist. It is important to note that even if one did not want to recognize the importance of change in economic policy and individuals' forecasting strategies, omitted variables alone can lead to temporal instability of estimated economic relationships.[73] To draw reasonable inference, therefore, it is crucial that I allow for structural change in my regression analysis.

The chapter is organized as follows. Section 2 develops a theoretical model based on IKE to base the econometric investigation on. Section 3 presents the procedure for testing for temporal instability. Section 4 presents the results from the structural change tests, discusses the methodology employed and compares the results to the *Bloomberg* analysis. Section 5 concludes.

4.2 From a Theory to an Empirical Model

Recall from Chapter 1 that the Frydman and Goldberg (2007, 2012) model of asset price swings and risk implies the following equilibrium condition for the stock market:

$$\hat{r}_{t|t+1} = \widehat{pr}_{t|t+1} \tag{1}$$

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[73] Economists are often constrained in which variables may be included in their empirical models whether because of data availability or because he omits then unknowingly. However, omitted variables may introduce temporal instability onto the model if the correlations they share with those variables which are included change over time.

where the variables are defined as before. Also recall, that the equilibrium condition in (1) results from equating the total supply and demand of bulls and bears in the marketplace. Rearranging gives us an equation for the price of stocks:[74]

$$lnP_t = ln\hat{P}_{t|t+1} - r_t^f - \widehat{pr}_{t|t+1} \qquad (2)$$

The IKE model assumes that the market's forecast of $\hat{P}_{t|t+1}$ can be expressed as:

$$ln\hat{P}_{t|t+1} = \beta_t^p lnP_t + \beta_t^X X_t + \varepsilon_t \qquad (3)$$

where X is a vector of fundamentals and β_t^p and β_t^X are time-varying parameters and ε_t is an i.i.d. error term. The IKE model relates the market premium to the gap:

$$\widehat{pr}_{t|t+1} = \beta_t^{gap}(lnP_t - lnP_t^{BM}) \qquad (4)$$

where P_t^{BM} is the benchmark price and β_t^{gap} is also time-varying. Plugging (3) and (4) into (2) and rearranging yields:

$$lnP_t = \frac{1}{\delta}\left[\beta_t^X X_t - \beta_t^{r^f} r_t^f + \beta_t^{gap} lnP_t^{BM} + \varepsilon_t\right] \qquad (5)$$

where $\delta = \left(1 - \beta_t^p + \beta_t^{gap}\right)$.

4.2.1 Choice of Variables

The *Bloomberg* analysis from Chapter 3 revealed that certain fundamental considerations merited the attention of market participants considerably more frequently than others. Referring back to Table 3.4, we can see that the

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[74] Dividends are excluded from the equation for expected return without altering the implications of the model.

fundamentals with the highest overall factor frequencies are: earnings (65%), the economy (47%), interest rates (38), sales/revenue (23%), company variables (23%), inflation (20%), oil prices (19%), ROW (14%) and gap/valuation (12%).

Several issues immediately appear as cumbersome in conducting econometric analysis on the basis of these fundamental factors. Equity market sales data availability is sparse and does not cover longer historical periods. The category of company variables is problematic because it includes fourteen disaggregated fundamental considerations and it is not clear that any one of them constitutes an overwhelming majority of the category's overall frequency. And, the category for ROW, by design, is infeasible to consider.[75]

However, there is widespread data available for the remaining fundamentals: earnings, the economy, interest rates, inflation, oil prices and gap/valuation.[76] The choice of data for earnings was straightforward. I use the aggregate S&P 500 Composite Indexed earnings. This data has been meticulously generated going back to 1871 by Robert Shiller at his website.[77]

For the economy, there are many data that capture different measurements of economic activity. A prime candidate is GDP. However, this measure is only released at a quarterly frequency. As such, industrial production, which is released at monthly frequencies, is used. Industrial production is an appropriate measure of economic activity because movements in the index

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[75] Recall that the Rest of World category includes any fundamental consideration mentioned in the other categories but pertaining to a foreign country. This puts an upper bound of 89 potential fundamental factors to be included in this category.

[76] A detailed description of the data is provided in the appendix. Graphs of these variables are presented in Figure 4.1.

[77] The data are taken from Shiller (2000b) and are updated at www.robertshiller.com.

represent the majority of variation in real output over the stages of the business cycle.

The choice of interest rate variable to include in the econometric analysis also requires some consideration. There was mixed evidence from the *Bloomberg* data as to which interest rate was deemed most important to market participants: bills, notes or bonds. I follow convention in using a short-term interest rate. I selected the three-month Treasury bill rate for the analysis. Selecting the respective data series' for inflation and oil prices was straightforward. I used the CPI and Producer Price Index for Crude Petroleum, respectively.

The final variable that the *Bloomberg* stories revealed as meriting market participants' attention relatively frequently was the gap/valuation consideration. The *Bloomberg* analysis provides evidence that, when individuals pay attention to the deviation of current prices from historical valuation levels, the price-to-earnings ratio is used as the benchmark (see Chapter 3). The market wrap from July 7, 1997, for example, reads, "Many investors are uncomfortable with the market's price-to-earnings ratio, which is near the high end of its historic range". The price-to-earnings ratio as a measure of stock market valuation relative to historical levels has also been used extensively by leading financial economists (Siegel, 2002; Shiller, 2005).

However, the choice of gap measure is superfluous in this case because the reduced form solution for the stock price in equation (5) leaves the

benchmark price on the right-hand side.[78] Moreover, the chosen measure for the

benchmark price is based on an essentially flat price-earnings ratio (see Figure

1.1). Though I follow Frydman and Goldberg's (2007, 2012) IKE model of the

market premium, I plan on investigating other factors that may proxy for risk in

equity markets in future research.

4.2.2 An Empirical Specification

Hypothesis testing based on variables that follow a unit root process lead

to invalid inference; relationships are found to be significant when really no

relation exists. This "spurious" regression problem complicates traditional

econometric analysis since most macroeconomic and financial time series data

are characterized as following unit root processes (Nelson and Plosser, 1982).

To deal with estimating a model which contains unit root variables, I use an

autoregressive distributed lag (ADL) specification of order two:[79]

$$P_t = \alpha_0 + \sum_{k=1}^{2} \alpha_k P_{t-k} + \sum_{j=1}^{6} \sum_{k=0}^{2} \beta_{kj} X_{j,t-k} + \varepsilon_t \tag{6}$$

where k denotes the number of lags on the dependent and independent

variables P and X respectively and j denotes the number of explanatory variables

to be included and β is a vector of coefficients.

If the variables included in an ADL specification are found to share a

cointegrating (equilibrium) relation, then the ADL model may be expressed in

error correction form and estimated (see Chapter 5). The benefit from starting

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[78] To see how the benchmark price is calculated see the data appendix.

[79] See Hendry and Juselius (2000) for a treatment on how the dynamic ADL model deals with relationships involving unit-root variables.

with the ADL model is that it maintains many of the shorter run dynamics which characterize the data generating process. Since, with cointegrating relationships, the ADL model is equivalent to the error correction model, both the shorter run and longer run dynamics of the fundamental relations are maintained, thus providing a richer portrayal of the dynamics of the underlying relation.

4.3 Recursive Tests for Structural Change

There is no completely objective way to test for temporal instability in fundamental relationships. The advancements in modern statistical techniques have produced an array of approaches to test for the constancy of parameters. As a result, different structural change tests will lead to different conclusions about the extent of the temporal instability in the causal process and the location of the breakpoints.

Both the *Bloomberg* data and the IKE model imply that fundamental relationships undergo change at times and in ways that do not follow any mechanical rules. To test for temporal instability, therefore, I use the CUSUMSQ test for structural change of Brown, Durbin and Evans (1975) (BDE). This procedure allows for such non-mechanical change in the data by searching recursively for parameter instability.[80] As such, this approach leaves open when and how change in the causal process may occur.

The recursive CUSUMSQ test of BDE has several benefits over extant approaches to testing for temporal instability. It is an improvement over the

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[80] For a review of the use of recursive techniques in structural change analysis, see Dufour (1982).

sample-splitting Chow-type tests that rely on imposing the breakpoint *a priori* (Chow, 1960). Moreover, unlike the Bai and Perron (1998, 2003) structural change test, the CUSUMSQ test allows for unit roots in the regressors.

To see how the CUSUMSQ test works, consider a linear regression model, with k regressors, of the form,

$$y_t = \beta' x_t + u_t \tag{7}$$

where y_t is the dependent variable, x_t is a vector of explanatory variables and u_t is an i.i.d. error term with mean zero and constant variance, σ_u^2. The test is based on estimating (7) over an initialization period equal to k. At period $t = k + 1$ the estimates $\hat{\beta}_{t-1}$ are used to forecast the dependent variable at time t, y_t. The resulting forecast error, $\hat{u}_t$, is the recursive residual and is defined as,

$$\hat{u}_t = \frac{(y_t - \hat{\beta}'_{t-1} x_t)}{f_t} \tag{8}$$

where,

$$f_t = (1 + x'_t (X'_{t-1} X_{t-1})^{-1} x_t)^{1/2} \tag{9}$$

and X_{t-1} contains all information based on explanatory variables up to and including period $t - 1$. The recursive residuals are generated in a sequential fashion through the end of the subsample, squared and cumulated, hence the term CUSUMSQ. Given a sample with T observations, the CUSUMSQ series is expressed as,

$$\max_{k+1...T} \sqrt{T} \left| S_T^{(r)} - \frac{r-k}{T-k} \right| \tag{10}$$

where

$$S_T^{(r)} = \frac{(\sum_{t=k+1}^{r} \hat{u}_t^2)}{(\sum_{t=k+1}^{T} \hat{u}_t^2)} \tag{11}$$

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Under the null hypothesis of parameter constancy, i.e. no structural change, the expected value of the CUSUMSQ series should fluctuate randomly around the 45 degree line. BDE construct confidence bands above and below the expected value line corresponding to a fixed significance level which, if intersected by the CUSUMSQ series, results in a rejection of the null and indicates a structural break has occurred prior to the intersection.

There is a rather large literature examining the power properties of the CUSUMSQ test and its close cousin, the CUSUM test (Brown et al., 1975). Early studies investigating the local asymptotic properties of the CUSUMSQ and CUSUM tests found the former to have only local trivial power (power equal to size) and the latter to have non-trivial local asymptotic power (Ploberger and Kramer, 1990). This finding initially substantiated the claim that of the two, the CUSUM test has the greater power and thus should be employed.[81] Recent evidence, however, suggests that this conclusion be overturned (Deng and Perron, 2008).

Unlike the analysis of Ploberger and Kramer (1990), Deng and Perron (2008) take a non-local approach and show that in finite samples, the power functions of the two tests yield drastically different results under varying model specifications. Simulation techniques show that under large breaks, or mean shifts, the CUSUMSQ test is found to be superior to the CUSUM test in a dynamic framework such as equation (6). That is, if a structural break is present, the CUSUMSQ test has monotonic power that increases with the magnitude of

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[81] In general, both tests are found to have low power relative to other structural change tests. That is, there is a relatively high probability of committing a Type II error – accepting the null hypothesis of no structural change when indeed a break has occurred.

the break, whereas the CUSUM test has non-monotonic power which decreases with the size of the break.

Furthermore, if a lagged dependent variable is included to correct for serial correlation across error terms, the power of the CUSUM test may decrease even further (Vogelsang, 1999). The study of Perron (2005) shows, through simulation analysis, that this is not the case for the CUSUMSQ test.

Recall, however, that the CUSUMSQ test is a test for structural change and as such, does not identify the most likely breakpoint. To address this problem, a sequential F-test is employed up to the point where the CUSUMSQ series intersects either of the significance bands. This is equivalent to estimating a Chow test at every point in time.[82] The most likely breakpoint is identified as the point corresponding to the largest F-statistic.

4.4 Structural Change Test Methodology

Most structural change tests suffer from loss of power when there exists multiple breakpoints that exceed those specified under the alternative (Vogelsang, 1999; Perron, 2006). Since the alternative hypothesis in the CUSUMSQ test is a one-time break, its power decreases with the sample length if more than one break is present. As such, the methodological approach taken in testing for structural change and locating the most likely breakpoints, involves analyzing subperiods of the data in a forward-looking fashion starting at the beginning of the sample. The procedure is as follows.

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[82] The 1-step Chow test is generated in PcGive and is equal to: $F_{1-step} = \frac{(SSE_t - SSE_{t-1})(t-k-1)}{SSE_{t-1}}$.

Beginning in 1959:03 the ADL model is estimated by OLS for the first 5 year period. If a break is detected by the CUSUMSQ test, the sequential F-test is used to locate the break. The model is re-estimated after this point and the procedure is repeated. If no break is detected during the first 5 years of the sample, I check for change during the first 10 years and, if no change is found, then during the first 15 years.

To find the first breakpoint, I did the following.[83] Since the ADL model is of order two, I estimate it over the first 5 year period starting in 1959:03. The CUSUMSQ test indicated a break at or before 1961:09. I then generate the sequential F-test based on the ADL model from 1959:03 to 1961:09. The highest F-statistic, and thus the first breakpoint, is found at 1961:09. Next, I run the CUSUMSQ test for the next 5 years starting in 1961:12, so as to not include the breakpoint in the ADL model of order two. The CUSUMSQ test indicates a break at or before 1965:06. Next, I run the F-statistic from 1961:12 to 1965:06 and find the most likely breakpoint at 1965:04. I follow this procedure throughout the end of the sample period at 2009:06.

4.4.1 Structural Change Results

The results of my structural change analysis are reported in Figure 4.16. I find 14 breakpoints over my sample, thereby implying 15 subperiods or regimes of "statistical" parameter stability.

What causes individuals to revise their forecasting strategies is an important and interesting question. We can imagine that such change

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[83] Plots of the CUSUMSQ and sequential F-tests are found in Figures 4.2-4.15.

corresponds to changes in policy or other important historical events. Indeed, other studies find this to be the case (Frydman and Goldberg, 1996).

Many of the breakpoints found in my analysis correspond with major historical events, such as institutional and regulatory changes as well as changes in the trajectory of the economy. For instance, the break at 1973:08 matches both the first OPEC oil shock and the beginning of the NBER dated economic recession in 1973:Q4. In addition, the break at 1981:09 also corresponds with the beginning of the U.S. recession in 1981:Q3. Based on the breakpoint at 1984:08, market participants may have anticipated the massive global currency market intervention of the Plaza Accord in 1985:09. Led by France, West Germany, Japan, U.S. and the UK, coordinated foreign exchange operations triggered a dramatic devaluation of the U.S. dollar which experienced a depreciation of 51% from 1985-87. The break in 1987:09 matches up roughly with the Savings and Loan Crisis following the Tax Reform Act of 1986.

Other breakpoints identified in my analysis correspond to reversals in stock price swings. The break found at 1981:09 aligns with the period where the S&P500 Composite Index price-to-earnings ratio reversed from a low, commencing one of the longest historical stock market upswings lasting until December 1999. The highest peak of valuations for the S&P500 Composite Index (44.2) in 1999:12 corresponds almost precisely to the break found at 1999:11. Many researchers associate this period with the collapse of the technology driven upswing in valuations of the late 1990's. The break in 2003:02 aligns perfectly with the turning point of the S&P500 Composite Index price-to-

earnings ratio, inaugurating the subsequent housing and equity expansion.

Finally, the break at 2006:10 lags the reversal and prolonged collapse of U.S.

housing prices by several months.[84]

However, we would not expect all of the breakpoints identified in the

structural change analysis to correspond to institutional and policy-related events

or reversals in price swings. The precariousness of market participants'

knowledge of fundamental relationships, and how they unfold over time, leads to

changes in trading behavior, and thus movements in such relations, that cannot

be fully foreseen.

Moreover, it would be very difficult to adequately capture such change, as

that found in this chapter, with an overarching mechanical rule. To do so would

require the ability to predict new Fed Chairmen and oil crises, etc.

4.4.2 The Structural Change Results and *Bloomberg* Stories

In Chapter 3, the *Bloomberg* stories provided evidence that different

fundamentals matter during different periods. In addition, evidence showed

variation in market participants' interpretation of the impact of movements in

fundamentals on the stock price. In particular, directional relationships involving

the economy and oil prices and the stock market price shifted from positive to

negative, and vice versa, at various periods from 1993-2009 (see Chapter 3).

Here, I compare the periods of change in the directional relationships based on

the *Bloomberg* data with those based on formal econometric tests for structural

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[84] The actual peak of housing prices was in 2006:04 based on the Case-Shiller Composite U.S. Housing Price Index, http://www.standardandpoors.com/indices/sp-case-shiller-home-price-indices/en/us/?indexId=spusa-cashpidff--p-us---- .

change found in this chapter. The results from both analyses are plotted in Figure 4.17 for the period January 1993 – June 2009.

The synchronization of the points of instability is immediately evident. Four out of five of the points of temporal instability correspond roughly across analyses. Both the structural change results and the *Bloomberg* analysis find a "breakpoint" at 1994:05. The directional shift in oil prices at 2002:11 is just three months apart from the structural break identified at 2003:02. Similarly the periods of instability during 1999-2000 and 2006-2007 are just months apart. To be sure, however, a different analysis of the *Bloomberg* data would likely lead to different points of change just as different econometric tests for temporal instability would. However, the correspondence of results from both analyses does strengthen their conclusions.

4.5 Conclusion

The econometric analysis presented in this chapter made use of the *Bloomberg* data in specifying an empirical model of short-term stock price movements. This chapter provided further evidence that the causal process driving short-term stock price movements is temporally unstable. The structural change results reported here and those of Chapter 3 that were based on the *Bloomberg* data, show a considerable degree of correspondence. Whatever one might think about the limitations of both types of structural change analyses, together the results provide rather strong support to the view that the causal process is temporally

unstable and that this instability is unlikely to be adequately captured by a

mechanical rule.

CHAPTER V

STOCK PRICES AND FUNDAMENTALS:
PIECE-WISE COINTEGRATION AND OUT-OF-SAMPLE FIT

5.1 Introduction

The failure of the REH-based canonical model to account for the tendency of

stock prices to undergo wide swings away from and toward estimates of

benchmark levels has led many economists and non-economists alike to believe

that these prices are often driven by pure psychological considerations and

technical momentum trading. Empirical studies seem to support this view: when

they estimate REH models, they find little evidence of a connection between

short-term stock price movements and fundamentals.

For example, Flood and Rose (2010) (FR) examine the out-of-sample

forecasting performance of several REH models using monthly data, including

the Gordon-growth model. This exercise estimates structural models and then

attaches these coefficients to actual future fundamentals. The out-of-sample fit is

then assessed based on measures of the forecasting error. FR find that these

models do no better than a random walk model even when they are given the

actual future values of fundamentals.[85] This failure of REH models, which was

first reported by Meese and Rogoff (1983) (MR), in the context of currency

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[85] For other studies that find little or no connection between short-term stock price movements
and fundamentals, see Welch and Goyal (2008) and references therein. For the failure to find a
fundamental relationship in currency markets see Sarno and Taylor (2002) and references
therein.

markets, suggests that fundamentals do not matter at all for short-term asset price movements.

The Frydman and Goldberg (2007, 2012) model of asset prices and risk provides an alternative explanation of the long-swings tendency of asset prices and the empirical evidence suggesting that fundamentals do not matter for short-term movements in asset prices. The model implies that long swings arise not because psychological maladies cause market participants to ignore trends in fundamentals in forecasting, but because they have imperfect knowledge of how to interpret these factors in thinking about the future. The IKE model also implies that while trends in fundamental factors drive short-term asset prices, this connection changes at times and in ways that do not conform to any mechanical rule. Consequently, empirical studies that ignore the problem of temporal instability, such as FR and MR, are likely to find little or no evidence of the importance of fundamental factors in driving markets.

Chapter 3 analyzed a novel dataset based on information contained in *Bloomberg* stories and found evidence supporting the IKE view over the bubble view of markets: fundamentals are the main drivers of daily stock price movements and the connection between stock prices and fundamentals changes in ways that no one can fully foresee. Chapter 4 provided econometric evidence of the IKE view that the causal process underpinning stock prices is temporally unstable. Both the informal *Bloomberg* analysis and the econometric analysis have serious limitations. However, Chapter 4's finding that the structural change

results of these analyses are similar, gives greater confidence to the conclusion that fundamentals matter, but in different ways during different time periods.

In this chapter, I provide additional econometric evidence on the IKE view and the importance of fundamentals for short-term stock price movements. To this end, I use regression analysis to examine the connection between monthly stock price movements and fundamentals within the separate subperiods of statistical parameter stability that I identified in Chapter 4. The idea is that, although we would not expect one fixed fundamental relationship to account for stock price movements over many decades, there may be stretches of time that are characterized by distinct and relatively stable fundamental relationships. That is, a piece-wise linear empirical model may provide an adequate approximation to relationships in the data.[86]

In examining the fundamental relationships in the linear pieces of the data, I undertake an in-sample cointegration analysis and an out-of-sample forecasting exercise. As in Chapter 4, the variables that I include in my composite empirical model are those that my *Bloomberg* analysis indicates are the most important in driving prices. Both the cointegration and out-of-sample forecasting analyses provide evidence supporting Chapter 3's conclusions based on the *Bloomberg* data. I find not only that fundamentals matter, but that different fundamentals matter during different time periods. Moreover, I present evidence that the problem with earlier empirical studies of stock prices is not just that they ignore

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[86] The methodology behind the empirical analysis of this chapter follows closely that of Goldberg and Frydman (1996) and Frydman and Goldberg (2007), which focus on modeling currency markets. One important difference, however, is that my study makes use of the *Bloomberg* data in specifying empirical models.

the problem of structural change, but that they restrict themselves to estimating empirical models that contain too few fundamental variables.

The chapter is organized as follows. Section 2 presents the unit roots tests for all of the variables in consideration. Section 3 presents the cointegration tests along with a specified error-correction model. Section 4 presents the out-of-sample-fit analysis. Section 5 concludes.

5.2 A Piece-Wise Linear Specification

The structural change results from Chapter 4 identified fourteen breakpoints, implying fifteen regimes of statistical parameter constancy over the period January 1959 through June 2009. The number of regimes over the sample period, however, presents the problem of low degrees of freedom so analysis is biased against finding a connection between fundamentals and stock prices.

Moreover, macroeconomic and financial time series data are routinely found to contain unit roots (Nelson and Plosser, 1982).[87] This feature of time series data may lead to distorted tests of statistical inference (Phillips, 1986). It is well known, however, that unit root and cointegration tests have low power against near-stationary alternatives.

The dynamic ADL specification addresses the problem of "spurious" regression in the presence of unit roots and near-unit root variables (Hendry and Juselius, 2000). In particular, the ADL specification allows for valid inference in econometric analysis because, if variables share a cointegrating relation, it is

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[87] See Footnote 5.

equivalent to the error-correction model which transforms all variables into stationary processes without sacrificing longer-run properties of the data.[88]

The piece-wise approach allows us to compare analyses across regimes of different lengths. The shortest regime of statistical parameter stability has 26 months (1994:06-1996:07) while the longest regime has 95 months (1973:09-1981:09). The cointegration analysis of this chapter, however, provides mixed results across regimes of varying length; cointegrating relations are found within regimes of both shorter and longer lengths. The forecasting experiment, however, does suggest a stronger connection between stock prices and fundamentals at longer horizons. Moreover, the results of FR are found to be both a consequence of not only including a narrow set of fundamentals, as instructed by REH, but from ignoring temporal instability in the causal process.

5.3 Stock Prices and Fundamentals as Unit-Root Variables

There is widespread evidence of unit roots in macroeconomic and financial time series data. Conducting traditional inference tests leads to invalid results or the "spurious regression" problem (Phillips, 1986). Distorted tests result from variables that share no relationship but do share some other trending commonality that might arise from such factors as economic growth or innovations in technology (Hendry and Juselius, 2000). As such, the variables appear to share a significant relationship when, in fact, there is none.

My analysis presents additional evidence that variables are nonstationary (have unit roots); they trend stochastically in an unbounded way. I circumvent

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[88] For details, see Banerjee *et al.* (1993) and references therein.

this problem by using the ADL specification and testing for a cointegrating

relation. The forecasting experiment of MR also deals with the issue of unit roots

because the procedure allows me to avoid the spurious regression problem

altogether.

5.3.1 Unit Root Tests

To conduct tests for cointegrating fundamental relations, the variables

must all contain at least one unit root. This subsection tests for unit-root

processes within the variables included in the dynamic ADL model presented in

equation (6) in Chapter 4. Testing for unit roots is complicated by the fact that the

traditional Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) unit root

tests suffer from size distortions and low power and are found to be very

sensitive to the specification of deterministic terms. The seminal papers of

Schwert (1989) and DeJong et al. (1992) used Monte Carlo experiments to show

that the size and power of both tests is compromised by the presence of large

negative moving average errors – which characterize the majority of

macroeconomic time series data.[89]

Much successful research has been devoted to developing both

modifications to these tests and alternative approaches to testing for unit roots.

This subsection incorporates a class of procedures, known as *efficiency* unit root

tests (Elliot, Rothenburg and Stock (ERS), 1996; Ng and Perron, 2001), which

are generally shown to improve upon the shortcomings of conventional ADF and

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[89] Though both studies reveal size distortions across ADF and PP tests in the presence of large negative MA errors, it is generally found that the ADF test has marginally greater power than the PP test.

PP tests.[90] Most notably, this class of unit root tests improves on both the size and power properties of both the ADF and PP tests. The unit root test results for the seven variables are reported in Table 5.1.[91]

By construction, all efficiency unit root tests include either a constant or a constant and a deterministic trend. As such, both scenarios are considered for each variable. Lag length selection for all tests is based on the Schwartz Information Criterion (SIC). The results reported in Table 5.1, strongly suggest the presence of unit roots in the time series data.

All three tests find the log of the S&P500, industrial production and oil price to be I(1); the variables are integrated of order one, implying that they require first-differencing to obtain stationarity. The null of a unit root cannot be rejected for the log of earnings for all tests except one of the Ng and Perron test statistics with a linear trend. Interest rates are found to be I(1) in all but the ERS Point Optimal test and one Ng and Perron test statistic, both including a constant – where the null of a unit root is rejected at the 95% level. The inflation rate is reported as I(1) in all but the DF-GLS case with drift where the null is rejected at the 95% level.[92]

Finally, we could reject the null of a unit root for the historical benchmark level only when a linear trend was included. This is not surprising as this variable

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[90] The tests employed are the DF-GLS and Point Optimal tests of Elliot, Rothenburg and Stock (1996) and the modified PP test of Ng and Perron (2001). For a detailed description of these tests the reader is directed to these corresponding papers.

[91] A first step to testing a variable's order of integration is graphical inspection. Visually, all seven variables appear strongly nonstationary (see Figure 4.1).

[92] The finding that inflation is I(1) is corroborated by evidence that prices are I(2). See Juselius (2007) for a broader discussion of this.

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is essentially a long moving average of the S&P500 price. Though not reported, all variables were able to reject the null of a unit root after first differences. These results support treating all variables empirically as I(1) processes.

5.3.2 Longer-Run Co-Movements of Stock Prices and Fundamentals

Do stock prices and fundamental factors co-move over the longer-run? If they do, this finding would support the IKE view that fundamentals matter for stock price movements. To address this question, I look at cointegrating vectors based on fundamental relationships. The IKE model and findings from Chapters 3 and 4 imply that different fundamentals matter during different time periods. Investigating whether cointegrating relations exist in a linear piece-wise fashion, is an approximate way to test for this.

This subsection investigates whether a longer-run fundamental relationship exists for the stock market within the regimes of statistical parameter constancy. As a first step, the ADL model from Chapter 4 equation (6):

$$P_t = \alpha_0 + \sum_{k=1}^{2} \alpha_k P_{t-k} + \sum_{j=1}^{6} \sum_{k=0}^{2} \beta_{kj} X_{j,t-k} + \varepsilon_t \qquad (1)$$

is tested for its residual properties within regime. The tests for normality, serial correlation and homoskedasticity are reported in Table 5.2. A notable feature of the table is that when the ADL model was estimated over the entire sample, assuming parameter stability, the residual properties violate many of the requirements for unbiased and efficient estimation. Within the regimes of statistical parameter constancy, however, the residual properties are well-behaved by a considerable margin relative to those assuming fixed-parameters.

As premised by the IKE model, this implies that fundamentals matter for stock prices once an allowance for temporal instability is made in changes to the causal process.

Differencing the data, though it renders stationary variables, suffers from the loss of longer run properties of the data. Testing the ADL model for a cointegrating relation provides a way to incorporate shorter run dynamics in the data generating process while simultaneously retaining its longer run features.

Intuitively, cointegration amongst variables results if a linear combination is found to be stationary. Engle and Granger (1987) define cointegration as follows. An $n \times 1$ vector x_t of series $x_{1t}, x_{2t}, \dots, x_{nt}$ is said to be integrated of order (d, b), denoted x_t $CI(d, b)$, if (i) all components of x_t are integrated of order d (stationary in d^{th} differences) and (ii) there exists at least one vector, $\alpha \neq 0$, such that $\alpha' x_t$ is integrated of order $d - b$, $b > 0$. Then, the vector α is called a cointegrating vector.

This subsection provides a battery of tests for cointegration in a single equation framework. The tests employed are the two-step procedures of Engle and Granger (1987) and Phillips-Ouliaris (1990), henceforth EG and PO, and the error correction mechanism (ECM) cointegration test of Banerjee *et al.* (1998). A battery of tests is employed because they are all predicated on different assumptions of how to represent the longer-run relationship and their respective treatment of serial correlation amongst the estimated residuals. The differences across tests will be discussed in greater detail below.

5.3.2.1 The Engle-Granger and Phillips-Ouliaris Two-Step Procedures

The EG and PO cointegration tests are both unit root tests of the estimated residuals from a static OLS regression (SOLS). The difference lies with the treatment of serial correlation in the estimated residual series. For both tests, the first step is to estimate a long run relationship by SOLS including p regressors,

$$y_t = \beta_0 + \beta_{it} x_{it} + u_t \qquad \text{for } i = 1, \dots, p \qquad (2)$$

The estimated residuals from this regression, $\hat{u}_t$, are then collected. Under the null hypothesis that the series $\{y_t, x_{it}\}$ are not cointegrated, there does not exist a linear combination which is stationary. This implies a unit root in the estimated residual series. Therefore, the rejection of a unit root in $\hat{u}_t$ directly implies the rejection of no cointegration amongst the series $\{y_t, x_{it}\}$. Thus, this unit root test is a test of a longer-run equilibrium relation. To account for serial correlation in $\hat{u}_t$ the EG test employs the ADF regression with ρ lags,

$$\Delta \hat{u}_t = a_1 \hat{u}_{t-1} + \sum_{i=1}^{\rho} a_{i+1} \Delta \hat{u}_{t-i} + \epsilon_t \qquad (3)$$

where $a_1 = \gamma - 1$ and γ is the size of the autoregressive root. Under the null of a unit root, $a_1 = 0$, and the series are not cointegrated. The EG test generates two statistics, a t-stat and a z-stat. The former is a direct t-test of the null hypothesis that $\gamma = 1$. The latter is based on the autocorrelation coefficient, $\hat{\gamma}$, normalized by $(1 - \sum_i \hat{a}_{i+1})$.

Unlike the EG procedure, the PO test corrects for serial correlation in estimating γ by first estimating a conventional unaugmented DF regression,

$$\Delta \hat{u}_t = (\gamma - 1)\hat{u}_{t-1} + \omega_t \tag{4}$$

Estimates from this regression are then used to construct the long run variance of ω_t given by $\hat{\lambda}_\omega$. The updated estimate of $\hat{\gamma}^*$ is referred to as the bias corrected autocorrelation coefficient, where,

$$(\hat{\gamma}^* - 1) = (\hat{\gamma} - 1) - T\hat{\lambda}_\omega (\textstyle\sum_t \hat{u}_{t-1}^2)^{-1} \tag{5}$$

The left-hand side term is then used to determine the t and z-statistics. Similar to the ADF and PP unit root tests, the EG and PO test statistics follow a nonstandard distribution which depends both on the number of regressors and included deterministic components. Moreover, the test statistics are further distorted because they are based on an estimated variable, $\hat{u}_t$.[93]

Though widely used, the residual-based unit root tests have been found to present several limitations – mainly arising from the assumption of a static longer run fundamental relation. It is widely known that if $\{y_t, x_{it}\}$ are cointegrated then the coefficients on the SOLS equation (2) are "super" consistent; they converge to their true values at a faster rate than otherwise (Stock, 1987). However, this long run representation ignores several features of the underlying fundamental relations which result in the tests having low power.

Kremers *et al.* (1992) trace the source of low power to the exclusion of dynamics when estimating the longer run relation in equation (2). For instance, the SOLS equation (2) is equivalent to the dynamic ADL model in the longer run for some *common factor* restrictions (see Appendix). The static OLS representation, however, may be biased in finite samples by ignoring the shorter

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[93] MacKinnon (1996), utilizing surface response simulations, provides critical values for the single equation residual based unit root test statistics for several combinations of deterministic terms and a wide range of regressors.

run dynamics (Banerjee *et al.*, 1993). As a result many researchers have proposed cointegration tests based on a reformulation of the error correction model (Benerjee *et al.*, 1998).

5.3.2.2 Cointegration Tests in a Dynamic Framework

Dynamic cointegration tests allow for short-run as well as longer-run dynamics in the fundamental relations. To address the loss of power from assuming invalid common factor restrictions in the longer-run relationship, Banerjee *et al.* (1998) propose an error-correction mechanism (ECM) test for cointegration in a dynamic framework that depends on the significance of the lagged dependent variable.[94] The error correction mechanism has the form:

$$\Delta y_t = \alpha' \Delta x_t + \beta(y_{t-1} - \lambda' x_{t-1}) + \varepsilon_t \tag{6}$$

where α, λ & x_t are $k \times 1$ vectors of parameters and explanatory variables, y_t is the dependent variable and β is a scalar. The set of variables $[y_t, x_t]$ are cointegrated if $-2 < \beta < 0$ and non-cointegrated if $\beta = 0$.

Banerjee *et al.* (1998) show that a test for cointegration between $[y_t, x_t]$ is equivalent to a t-ratio test of β from the unrestricted ADL model estimated by OLS:

$$\Delta y_t = \alpha' \Delta x_t + \beta y_{t-1} + \theta' x_{t-1} + \varepsilon_t \tag{7}$$

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[94] Testing for the significance of the lagged dependent variable is equivalent to testing the significance of the error-correction term in an error-correction model (Banerjee *et al.*, 1993).

Engle *et al.* (1983) show all that is required for OLS to be an asymptotically efficient estimation procedure in (7) is for x_t to be weakly exogenous.[95] Banerjee *et al.* (1998) provide the asymptotic critical values. For an ADL model of order two with six regressors, this amounts to testing the β^Y coefficient in,

$$\Delta y_t = \beta^Y y_{t-1} + \theta'_i \sum_{i=1}^{6} x_{i,t-1} + \alpha' \Delta y_{t-1} + \sum_{i=1}^{6} \phi'_i \Delta x_{i,t-1} + \varepsilon_t \qquad (8)$$

The ECM makes several notable improvements on the EG and PO two-step tests for a cointegrating fundamental relation. Since the ECM test is developed in a dynamic ADL framework it retains any of the short-run properties of the data generating process and as such, does not suffer from the low power properties due to invalid common factor restrictions. In addition, the test is not hampered by the size distortions due to large roots of the MA process as first observed by Schwert (1989). Banerjee *et al.* (1998) also show that the ECM test does not depend on nuisance parameters.

A battery of cointegration tests discussed above are collectively employed because they provide alternative representations of the longer-run equilibrium fundamental relation. Since it is difficult to judge which representation is the better candidate, results from the three tests are all considered. The results from the EG and PO two-step procedures are reported in Table 5.3 while the results from the dynamic ECM test are reported in Table 5.4.

The results from the three cointegration tests find a significant longer-run fundamental relation in nine out of the fifteen regimes of statistical parameter

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[95] The ADL model of order two is found to be sufficient in generating white noise residuals within the regimes of parameter constancy. As such, the leads of the regressors are not added to the ADL model as suggested by Banerjee *et al.* (1998) and the regressors are deemed weakly exogenous.

constancy. As implied by the *Bloomberg* data and IKE models, the tests show that fundamental factors matter for stock prices and that different fundamentals matter during different periods

5.3.3 An Error-Correction Model

Another way to investigate whether the IKE models' implication that fundamentals matter for stock prices is to specify an error-correction model.[96] The model is based on the specification in equation (6) of order two. Error-correction models allow for valid inference testing amongst the included variables and provide a coefficient of "error-correction" representing the speed, if any, of adjustment back toward equilibrium. In order for the equilibrium adjustment to occur, the coefficient on the lagged residual (the term in parentheses on the right-hand side of equation (6)) must be negative and significant. To capture this term, the lagged residuals from the long-run ADL model are included. This approach is found to capture both the short-run as well as longer-run properties of the data generating process and is preferred to other long-run residuals, such as those based on a static relation (Hendry and Juselius, 2000).

Table 5.5 reports the results from the error-correction model within the cointegrated regimes. All of the lagged residuals are found to be negative and highly significant with varying degrees of error-correction. Moreover, many of the variables are found to be significant within regimes, but the signs of the coefficients are mixed with respect to conventional economic theory. To test the

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[96] The Engle-Granger Representation Theorem states that cointegration and error-correction are equivalent approaches to testing for a longer-run fundamental relation.

error-correction specification further, Table 5.6 examines the residual properties of the model within regime. Although serial correlation is present in some subperiods, the normality properties are satisfied within every regime at the 5% significance level.

These results add further evidence to the IKE view that fundamentals matter for stocks prices but in different ways during different periods.

5.4 Out-of-Sample Fit

Another approach toward investigating whether fundamental considerations matter for stock price movements in the presence of unit roots, is to test a model's out-of-sample fit. By its nature, this approach does not rely on inference testing and as such, avoids the spurious regression problem altogether. The seminal study of Meese and Rogoff (1983) found that the out-of-sample fit for exchange rate determination models could not beat that of the simple random walk. This result maintained even though information about actual future values of the explanatory variables was used. The results implied that the predictive power of the structural models could not outperform a naïve model whose prediction was equivalent to that of a coin-toss.

This was a devastating blow to the field of international finance and is still widely discussed in academic circles today. The purpose of this subsection is to test whether fundamentals matter for stock prices. This is accomplished by extending the MR methodology to the stock market to test the out-of-sample fit of a fundamentals-based model to that of the random walk. As with the

cointegration tests, this analysis is conducted within the regimes of statistical parameter stability.

The MR methodology is as follows. The model is estimated during an initialization period, say from t to $t+k$. The coefficients generated from the estimation period are then used to forecast the K-month horizon asset price, where K=1,3,6 and 12. In order to carry-out this procedure, forecasts of the future explanatory variables must be generated. To give the structural models the benefit of the doubt, actual future realizations of the explanatory variables are used to append to the coefficients from the estimation period.[97] The model is then updated with the $t+k+1$ observation and the procedure is repeated throughout the end of the sample period.

It is common to assess the out-of-sample fit of the various models through root mean square error (RMSE), mean absolute error (MAE) and mean error (ME). RMSE is the preferred criteria since it produces the standard deviation of the forecast error. The MAE and ME, however, are also useful in that they may decipher whether or not the model consistently under or over-predicts. But what really matters for financial practitioners is not how large the error is, but rather whether or not they chose the right side of the market. As such, this analysis incorporates direction of change statistics (DCS) measuring the percentage of time the model predicts the right side of the market.[98]

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[97] The rationale was that the structural exchange rate determination models were able to predict future prices well but struggled in predicting the future explanatory variables. See Meese and Rogoff (1983).

[98] The significance of the DCS can be evaluated by a binomial distribution.

The recent study of Flood and Rose (2010) investigates the same question as this subsection. The authors compare a battery of random walk and time series models to three versions of the Gordon growth model (Gordon, 1962) — a dividends-based model, an earnings-based model and a composite model incorporating dividends, earnings and short-term interest rates.[99] The results of FR are very similar to the original MR study leading the authors to conclude,

> In this sense, domestic financial prices of great interest (stock market indices) are just as difficult to forecast as international financial prices (exchange rates). International finance seems to be no worse at modeling important asset prices than domestic finance, at least over the MR sample period (p. 12-13).

As with many empirical asset pricing studies, the results of FR (2010) are most likely due to two related factors. First, the REH-based Gordon growth model is constrained by the inclusion of few fundamental factors. Second, the model presumes a fixed parameter environment.[100] This subsection attempts to address these issues.

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[99] FR (2010) follow the same sample period as Meese and Rogoff (1983). The initial estimation period runs from March 1973 through November 1976 and the forecasting period runs from November 1976 through June 1981. To account for the possible effects from presidential elections, FR (2010) change the forecast start date from November 1976 to November 1978. For the same reason they change the end of the forecasting period to November 1980. The authors also run an estimation period through March 1989 and a forecasting period up to December 2001. The authors test the random walk with and without drift as well as other univariate and vector autoregressive (VAR) time series models. For the structural models the authors incorporate ordinary least squares (OLS), instrumental variables (IV), least absolute deviation (LAD), generalized least squares (GLS) and OLS with seasonal dummies. In addition to the US equity markets, FR (2010) also investigates the Japanese, United Kingdom and German equity markets. The results are all consistent with the findings of Meese and Rogoff (1983).

[100] Even though there was only one break identified in Chapter 4 (1973:08) that falls within the sample of MR and thus FR (2010), the models under question are different. In addition, there is no objective way to test for structural change. Here, I am arguing that FR (2010) does not formally consider the issue of temporal instability. Furthermore, I estimate a FR Gordon-earnings model over the MR sample with and without the breakpoint identified in my structural change analysis (see Table 5.7). Unsurprisingly, their results based on RMSE are improved upon once temporal instability is accounted for.

To carry-out the Meese and Rogoff (1983) analysis for the stock market, a reformulated error correction model is utilized:

$$P_{t+K} = P_{t+K-1} + \hat{\alpha}_K \left(\hat{\beta}_K X_{t+k-1} - P_{t+K-1} \right) + \sum_{i=1}^{6} \hat{\gamma} \Delta X_{i,t+K} \qquad (9)$$

where

$$\hat{\beta}_K X_{t+k-1} - P_{t+K-1} = \hat{u}_{t+K-1}^{LRADL} \qquad (10)$$

denotes the estimated residual from the long-run solution to the ADL model (see Appendix). The out-of-sample fit based on equation (9) is compared to that of the pure random walk and random walk with drift models. The Gordon Growth earnings-based model from FR is also used for comparison.[101] The results are reported in Table 5.7.

The structural error-correction model is found to outperform the random walk models in virtually every regime of parameter constancy based on RMSE.[102] This finding is considerably more pronounced at longer horizons. For instance, the root mean square error generated by the error-correction model was on average 35 percent lower than that of the pure random walk. However, using RMSE as a performance criterion masks the more practical concern in predicting the right side of the market.

In capturing this motive, the DCS show that the ability of the error-correction model to predict the right side of the market also increases at longer horizons. The percentage of correct predictions at the six and twelve month

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[101] The Gordon-Earnings model is generated using a 3-month forward-looking growth rate of earnings as in FR (2010). These statistics are roughly equal to those generated by FR (2010); even though the data source of earnings is the same, FR (2010) generate earnings from backing them out of the price-to-earnings ratio whereas I collect the earnings data directly from the data source. See www.robertshiller.com.

[102] MAE and ME are also generated with similar results and therefore are excluded for brevity.

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horizons were on average 75 and 94, respectively. In addition, the structural

model is found to outperform the Gordon earnings-based model in virtually every

regime at each forecasting horizon.

There are two sources of poor forecasting performance for FR's Gordon-

earnings model. The model may suffer because: REH selects a narrow range of

fundamental factors that individuals use in forecasting, and/or because the model

does not take into consideration temporal instability of the causal process. Table

5.7 shows results for the FR model over the original MR sample with and without

the breakpoint identified in my structural change analysis. Unsurprisingly, the

results based on RMSE are improved upon once temporal instability is

accounted for. This finding, in addition to the overwhelming improvement of the

structural error-correction model relative to the FR Gordon-earnings model,

suggests that both issues limit the performance of the REH-based model.

The results from this subsection provide more evidence consistent with

the IKE models' implication that fundamentals matter for stick prices. In addition,

the IKE implication that individuals pay attention to different fundamentals at

different periods when forecasting is shown to be a source of limitation of a

traditional REH-based stock pricing model.

5.5 Conclusion

In general, the statistical evidence from the out-of-sample fit from this section and

cointegration analyses from the previous section support the IKE implication that

a fundamental relationship is operating in the equity market once temporal

instability is considered. Moreover, the finding of a fundamental relation is more

prominent at longer horizons.

Appendix

A5.1: <u>The Common Factor Restrictions from ADL to Static Models</u>

Starting with the dynamic ADL model of order two presented in Chapter 4:

$$y_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i y_{t-i} + \sum_{j=1}^{6} \sum_{k=0}^{2} \beta_{kj} x_{j,t-k} + \varepsilon_t \qquad (A1)$$

The longer run equilibrium solution to equation (A1) implies:

$$y_t = y_{t-1} = y_{t-2} \qquad (A2)$$

and

$$x_{it} = x_{i,t-1} = x_{i,t-2} \qquad \text{for } i = 1 \dots 6 \qquad (A3)$$

Applying (A2) and (A3) to (A1) and rearranging yields,

$$y = \frac{\alpha_0}{(1-\alpha_1-\alpha_2)} + \sum_{i=1}^{6} \frac{(\beta_{i,0}+\beta_{i,1}+\beta_{i,2})}{(1-\alpha_1-\alpha_2)} x_i + \varepsilon_t \qquad (A4)$$

Next, consider the static representation of the same set of variables:

$$y_t = \theta_0 + \sum_{i=1}^{6} \theta_i x_i + \epsilon_t \qquad (A5)$$

Equation (A5) represents the longer run equilibrium relation for the static model.

For (A1) and (A5) to be equivalent representations of the longer run equilibrium

representation of the variables in question, requires:

$$\theta_0 = \frac{\alpha_0}{(1-\alpha_1-\alpha_2)} \qquad (A6)$$

and

$$\theta_i = \frac{(\beta_{i,0}+\beta_{i,1}+\beta_{i,2})}{(1-\alpha_1-\alpha_2)} \qquad \text{for } i = 1 \dots 6 \qquad (A7)$$

Equations (A6) and (A7) are the *common factor restrictions* required to for the

longer run equilibrium solution (A5) to be equivalent to the long-run solution (A4).

CHAPTER VI

BLOOMBERG STORIES AND FUNDAMENTALS:
WHEN DO THEY MATTER?

6.1 Introduction

Classical econometric analysis assumes that causal relationships are time-invariant. IKE models and the results from Chapters 3 through 5 imply, however, that the causal relationship underpinning asset price movements does not conform to a fixed mechanical rule; different fundamentals matter in different ways during different time periods. This chapter asks what considerations lead market participants to focus on certain fundamentals and not others during specific time periods.

One hypothesis that I examine is whether individuals pay greater attention to causal factors when they have moved dramatically over recent periods. The *Bloomberg* data on monthly factor frequencies of oil prices and inflation suggest that this may be the case. Another hypothesis posits that the weights market participants place on fundamentals in forecasting stock prices depend on deviations in the value of fundamentals from their *own* historical benchmark levels. A sub-hypothesis posits that the weights depend on which side of the benchmark the fundamentals are departing away from.

IKE models imply that revisions in individual forecasting strategies are an important factor in explaining reversals in asset prices. Under this account, market participants have a tendency to revise their forecasting strategies in

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guardedly moderate ways, adhering to existing ways to think about the future unless reason presents itself to do otherwise. By imposing only qualitative restrictions on the magnitude of revisions in individual forecasting strategies, IKE models allow for this regularity to be uneven and cease to exist at times that cannot be seen in advance. This portrayal of the way participants alter their thinking about the future allows for dramatic revisions in forecasting strategies, and thus price-swing reversals to occur.

The question remains, however, as to what may contribute to such drastic revisions in individuals' forecasting strategies. What causes individuals to pay attention to some variables and not others, and what precipitates this switch? To be sure, there are myriad possible reasons for this to occur, such as psychological factors, policy changes and changes in the social context. This chapter, with the use of my *Bloomberg* data, investigates the relationship between the degrees of attention certain variables merit by market participants in forecasting market outcomes and movements in the actual fundamental under question.

The incorporation of temporal instability in fundamental relations, as that implied by IKE models, is very troublesome for econometric analysis. One way to deal with this, as most researchers do, is to assume it away by estimating fixed-parameter models. As discussed in earlier chapters, the majority of models that do allow for change fully predetermine it. Even though IKE models stop short of fully predetermining change, there are certain qualitative regularities exhibited within the causal process that may be shown to hold for subperiods of data. This

view may be intertwined into more formal econometric analysis if, say, there was some evidence showing what circumstances dictate certain variables to matter during periods of time over others.

This chapter provides some evidence that may pioneer this union. There are two main findings of this chapter. First, individuals pay attention to fundamental factors when the value of the fundamental has deviated away from historical benchmark levels, i.e. the attention of certain variables merited by market participants co-moves with the gap. Moreover, the side of the benchmark from which the value of the fundamental is deviating is found to be important.

Second, evidence is provided showing that fundamentals matter for forecasting when they have moved dramatically in recent periods. Anyone routinely paying attention to financial market news outlets such as *Bloomberg*, *Reuters* or *CNBC*, would not find this surprising. Combined, these two pieces of evidence may usher-in a new approach to modeling temporal instability within econometric analysis.

This chapter is organized as follows. Section 2 presents the empirical analysis. Section 3 concludes.

6.2 An Empirical Analysis

My *Bloomberg* data suggest that the frequency with which certain variables merit attention by market participants in forming their forecasts of market outcomes, undergoes change which would be difficult to adequately capture with an overarching mechanical rule. The time series plots from the *Bloomberg* data for

oil prices, interest rates and inflation were among the fundamental factors to display this feature most prominently (see Chapter 3 and Figures 3.8, 3.9 and 3.10, respectively). Recall, however, that the factor frequency plots are not parameters or coefficients of fundamentals; they merely represent the frequency of attention generated by market participants. That this frequency displays such variation, suggests that there are other considerations at play.

In conducting this investigation, a first pass is to plot the factor frequency series based on the *Bloomberg* data against the fundamentals' actual time series data. Figures 6.1 and 6.2 plot this relation for interest rates and oil prices, respectively. The correspondence is striking.[103] For these fundamentals, the frequency with which market participants deem them relevant in forming their forecasts of market outcomes is a positive function of its actual univariate process.

This evidence may be interpreted in two ways. First, the importance individuals place on these fundamentals may be increasing because the factors themselves are undergoing considerable variation. Second, the attention being generated is due to the deviation of fundamentals from estimates of historical benchmark levels.

6.2.1 Fundamentals and Benchmark Levels

To tease out the alternative hypotheses, I apply a Hodrick-Prescott (HP) Filter (Hodrick and Prescott, 1997) to the actual time series data. This procedure

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[103] Oil prices data are taken from the Producer Price Index for crude petroleum. Interest rates are the 3-month Treasury bill rate and inflation is measured as the monthly change in the CPI. See data appendix for details.

is a smoothing method that generates a long-term trend in a data process. This is accomplished by minimizing the deviations of the actual time series data from the trend component in a non-linear fashion. As such, the trend component is a proxy for an estimate of a benchmark level for the fundamental factor. The magnitude of deviations away from the trend component, referred to as the cycle component, represents a proxy for the gap effect. The cycle component is plotted for oil prices and interest rates against their respective factor frequencies generated by the *Bloomberg* data in Figures 6.3 and 6.4.

The evidence suggests that the high correspondence illustrated in the earlier Figures 6.1 and 6.2 is due to the departure of fundamentals from historical benchmark levels. But, both figures show that the effect of the deviation is more pronounced from above rather than below. This suggests that more "unfavorable" gaps from benchmark levels, such as the negative impact from high oil prices and interest rates on consumers and firms, matter more than other less "favorable" gaps.[104]

Oil prices, for example, generated an escalated amount of attention beginning in mid-2004 just as the price of oil began an unprecedented upward expansion. Prior to 2004, the peak of crude oil prices reached 118 in October of 1990. In June of 2004 the price stood at 99.2, but by July 2008, just four years later, the price attained a new height at 384.3 – an increase of 287% over a four year period. To be sure, this evidence also points to the hypothesis that dramatic changes in the value of the fundamental factors dictate how important individuals deem them in forecasting market outcomes.

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[104] This is certainly an area of interest for future research.

For interest rates, a similar story emerges. Keynes (1936) was one of the earliest observers of the gap effect on interest rates. Recall from Chapter 1, in assessing the decision faced by market participants of whether to hold wealth in the form of cash versus interest-bearing bonds, Keynes (1936, p. 201) notes,

> [the demand for cash] will not have a definitive quantitative relation to a given rate of interest r, what matters is not the *absolute* level of r but the degree of its divergence from what is considered a fairly *safe* level of r, having regard to those calculations of probability which are being relied on.

Figure 6.4 suggests that market participants may have deemed short-term interest rates of 5%-6% to be away from "safe" levels. From 1993-2009 the 3-month Treasury bill reached such levels during the periods of 1995-1996, 2001 and 2006-2007. These periods of elevated rates, relative to recent history, align roughly with the peaks of factor frequencies based on the *Bloomberg* data and the peaks from the cycle component of the HP Filter in Figure 6.4. Based on this analysis, the conclusion to be drawn for oil prices and interest rates is that they generate considerable attention from market participants in forecasting stock prices when they are away from safe levels and, possibly for oil prices, when they have moved dramatically in recent periods. Moreover, the deviation from these benchmarks is heavily weighted from above relative to below.

6.2.2 Fundamentals and Growth Rates

A clearer story for the impact of recent volatility, however, emerges for the inflation rate. Figure 6.5 plots the monthly change in the Consumer Price Index against the factor frequency for inflation based on the *Bloomberg* data. The

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rough correspondence of these time series corroborates the alternative hypothesis that market participants place greater weight on certain factors if they have moved dramatically in recent periods.

That undesirable economic developments may have a greater impact on stock prices than good news has been a hypothesis previously investigated by economists (Veronesi, 1999). I take this conjecture a step further by incorporating my *Bloomberg* data with the objective of understanding what underpins the factor frequency for the economy.[105] In Figure 6.6, I plot the *Bloomberg* frequency series against a monthly measure of negative growth in the economy, utilizing time series data on Industrial Production. By marking the months which experienced a negative growth rate in this measure of the economy, the analysis appears to highly support the view that individuals pay attention to certain variables when they are exhibiting undesirable movements. This is also supportive of the evidence from oil prices and interest rates. When successive months of negative economic growth are experienced, market participants deem the economy more important when forecasting future stock prices.

6.3 Conclusion

The analysis carried out in this chapter provides a gateway to incorporate IKE models' implication of temporal instability in fundamental relations into more formal econometric analysis. The findings, lead to two main conclusions. First,

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[105] The time series plotted for the Economy is the original series prior to generating a 12-month trailing average.

the attention that certain fundamentals merit from stock market participants is positively related to the deviation of fundamentals from benchmark levels with the caveat that its impact is greater when the departure is deemed "undesirable."

Second, the variation in actual fundamental processes is also a consideration that contributes to the attention generated by market participants. That these main findings were corroborated across several fundamental factors strengthens the conclusions. These findings may shed light on new ways for incorporating temporal instability into econometric analysis and, as such, warrant further research.

CHAPTER VII

LONG SWINGS IN EQUITY MARKETS:
THE BUBBLE OR IKE APPROACH?

7.1 Introduction

Asset price behavior in financial markets is characterized by long swings away

from and toward estimates of common benchmark levels. Traditional REH-based

models, however, have failed to explain this endemic feature of markets on the

basis of fundamental considerations such as overall economic activity and

interest rates. This long-swings "puzzle" has led financial economists to develop

bubble and IKE models. Though both approaches argue that short-term

movements in the market's expectation of future prices is the primary driver of

long swings, they offer contrasting accounts for these movements.

Bubble models imply that pure psychological and momentum-related

considerations are the primary driver of expectations and thus of short-term price

behavior. In contrast, IKE models imply that fundamental considerations are the

main driver of expectations and stock price fluctuations, although in changing

ways that would be difficult to adequately capture with an overarching

mechanical rule. IKE models also imply that psychological considerations are

important in underpinning how individuals interpret trends in fundamentals as

they forecast future market outcomes.

The main research question of this thesis has been to determine which class of models provides the better account of short-term stock price movements on the basis of empirical evidence.

7.2 Overall Conclusions and Implications for Theory

The *Bloomberg* and econometric analyses provided evidence that fundamental factors are the primary driver of short-term stock price movements. Furthermore, both analyses showed that stock-price relations are temporally unstable and subject to change that would be difficult to capture with overarching mechanical rules. Psychological considerations were found to be quite important but when they mattered it was almost always in connection to a fundamental factor. Pure psychological and technical momentum-related considerations received virtually no support in underpinning short-term movements in equity prices. The resounding conclusion to be drawn based on the evidence of this thesis is that the IKE model provides a better account of short-term stock price movements, and thus long swings, in favor of the bubble account.

One of the original contributions of this thesis is the novel *Bloomberg* dataset which shed light on the more pragmatic characteristics of the processes underpinning stock price behavior. Two of the more salient features uncovered in the data are the wide range of causal factors reported as driving practitioners' short-term expectations and thus stock price movements and the variation in stock price relations. These findings suggest that stock and other asset pricing models may gain a clearer account of market dynamics by being inclusive of a

wider information set of causal factors. Moreover, both the *Bloomberg* and econometric evidence suggest that theoretical models, in the spirit of IKE, be open to non-routine changes in the causal process.

7.3 Policy Implications and Open Questions

The question of whether bubble or IKE models provide a better account of stock price movements has far reaching implications for policy in light of the recent financial crisis and the urgency for financial reform and a greater role for the state. The findings of this thesis add to the literature suggesting that speculation in financial markets is driven by trends in fundamentals and not akin to that of a casino. The evidence implies that the long swings inherent to stock and other asset markets are an important feature in allocating society's scarce capital in a productive way rather than haphazardly rationing it about. The conclusions of this thesis suggest that regulators refrain from curtailing such oscillations, unless they are deemed to be excessive, since the evidence suggests they are connected to trends in fundamentals.

Even though this thesis provided new ways to confront the implications of bubble and IKE models with empirical evidence, the literature investigating this direct comparison is relatively sparse and many questions remain open. How to capture the psychological influence on the market is and will always be an important yet tantalizing avenue of research which is still young in existence. The immature field of emotional finance may be fertile grounds for further research in this area. In addition, strides have been made towards testing the non-routine

importance of fundamentals for asset price behavior but much work remains to be done. Given the nature of the implications of both bubble and IKE models, future research on this topic is both substantially warranted and extremely useful for policy and reform of the financial system.

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Appendix
Description of Data

p	nominal S&P500 Composite Index price, monthly, collected from www.econ.yale/~shiller
ip	industrial production index, monthly, seasonally adjusted, collected from Board of Governors of the Federal Reserve System, Series ID:INDPRO
r^f	nominal interest rate, 3-month Treasury Bill: secondary market rate, monthly percent, Board of Governors of the Federal Reserve System,Series ID: TB3MS
e	earnings for the S&P500 Composite Index, monthly, collected from www.econ.yale/~shiller
π	Percent change in CPI Index for all urban consumers, monthly, Bureau of Labor Statistics
oil	crude petroleum (domestic production), monthly, collected from the Bureau of Labor Statistics, Series ID: WPU0561, not seasonally adjusted
bm	S&P500 Composite Index price to earnings historical benchmark, monthly, calculated as $\left[\sum_{i=0}^{(50\cdot12)-1} \left(\frac{P}{E}\right)_{t-i} / (50x12) \right] \times \sum_{i=0}^{9} E_{t-i} / (10 \cdot 12)$, this is based on the price to earnings ratio from www.econ.yale/~shiller which takes a 10 year moving average of earnings in the denominator

Table 3.1
Fundamental Factor Categorization Based on
Bloomberg News's Market Wraps
Sample Period: 1993:01-2009:12

Fundamental Factors			
Economy	GDP Index of leading economic indicators Industrial production Productivity Consumer income Service sector Employment (nonfarm) Unemployment rate Jobless claims Job creation Manufacturing Index Factory orders Durables Nondurables Construction spending	Housing	Housing starts Home sales Foreclosures Housing slump Real estate prices Mortgage rates Commercial property value
Interest Rates	Fed Funds Discount rate Treasury bills yield Treasury notes yield Treasury bonds yield	Oil	Crude oil prices OPEC oil supply
Inflation	Producer Price Index Consumer Price Index Manufacturing Price Index Wages	FEM	Value of dollar Value of foreign currency Introduction of Euro
Earnings	Earnings and profits	Sales	Revenues Retail sales Auto sales

.

Table 3.1 Continued

Gap/ Valuation	Distance from historical levels Overvalued Undervalued	Trade	Agreements (NAFTA/GATT) Tariffs Quotas Subsidies Current account deficit Current account surplus
Company Variables	Bankruptcy CEO or CFO leaves Malpractice, legal or accounting issues Firm added to index Firm market value added Dividends Mergers and acquisitions Book-to-bill ratio Firm layoffs or labor strike Stock split Share buyback Large stake in firm IPOs Business spending or investment	Government	Fiscal policy Administrative comments Taxes and rules on CEO bonuses Credit worthiness Stimulus plan Bailout Nationalization of banks or healthcare Budget surplus Budget deficit Political event or election Political conflicts, instability or corruption Armed conflicts or nuclear testing FDIC/SEC restructuring; regulations stress Tests Treasury secretary leaves
Central Bank	Monetary policy Minutes or comments Bailouts	Consumption	Consumer spending or demand Consumer confidence
Terrorism	General terrorism or attacks	Financial/ Credit Markets	Financial markets or sector Weakness in credit markets Credit ratings Lack of capital funding Credit card defaults Restructuring or regulation
ROW	All of the above factors as they pertain to the rest of the world		

Notes: CEO, chief executive officer; CFO, chief financial officer; FDIC, Federal Deposit Insurance Corporation; GATT, General Agreement on Tariffs and Trade; GDP, gross domestic product; IPO, initial public offering; NAFTA, North American Free Trade Agreement; OPEC, Organization of Petroleum Exporting Countries; ROW, rest of world; SEC, Securities and Exchange Commission.

Table 3.2
Psychological Considerations Based on
***Bloomberg News's* Market Wraps**

Psychological Factors
Optimism
Pessimism
Confidence
Sentiment
Greed
Fear
Concern
Euphoria
Crowd Psychology
Exuberance
Worry
Mania
Panic

Table 3.3
Technical Trading Considerations Based
on *Bloomberg News's* Market Wraps

Technical Trading			
Non-Momentum	Profit taking Firm added to index Holiday effect January effect End of month effect End of quarter effect Friday effect End of the year effect Giving back effect Triple witching Monday effect	Momentum	Market rally Market momentum Momentum traders Bandwagon Price-to-price loop Moving average Chartism

Table 3.4
Factor Frequency (1993:01-2009:12) Based
on *Bloomberg News's* Market Wraps

Factor Frequency (%)*		Relationship w/Stock Market Price
Fundamentals	99	N/A
Earnings	65(40)**	(+) 100%
Psychological considerations	55	N/A
Psychology with fundamentals	54	N/A
Economy	47(35)**	(+) 60%
Interest rates	38	(-) 98%
Sales	23	(+) 100%
Company variables	23	N/A
Inflation	20	(-) 98%
Oil	19	(-) 54%
ROW	14	N/A
Gap/Valuation	12	(-) 94%
Government	12	N/A
Consumption	12	(+) 82%
Central Bank	11	N/A
Housing	8	N/A
Technical Trading	6	N/A
Currency markets	6	(+) 66%
Financial or credit markets	6	N/A
Uncertainty	6	(-) 100%
Technical non-momentum	5	N/A
Bubble considerations	3	N/A
Technical momentum	2	N/A
Terrorism	2	(-) 100%
Trade	1	N/A
Pure psychology	1	N/A

Notes: *The values in the second column denote the proportion of days that each factor was mentioned in driving the aggregate market over the entire sample from January 4, 1993 – December 31, 2009. ROW, rest of world
**The value in parenthesis denotes the "direct" effect of the variable.

Table 5.1
Efficient Unit Root Tests
Test Statistics
Sample: 1959:01-2009:06

Variable[#]	x_t'	DF-GLS[*] ($t - stat$)	ERS-Point Optimal[d] (P_t)	(MZ_α^d)	(MZ_t^d)	(MSB^d)	(MP_t^d)
				NP[e]			
p	{1}	1.43	151.1	0.99	1.43	1.45	139.7
	{1,t}	-1.59	17.28	-5.28	-1.59	0.30	17.14
e	{1}	-0.38	32.82	-0.70	-0.55	0.78	30.61
	{1,t}	-2.43	7.87	-12.29	-1.79	**0.15[b]**	10.81
ip	{1}	2.00	445.39	0.91	2.10	2.32	338.7
	{1,t}	-0.81	25.67	-2.88	-0.87	0.30	23.50
i	{1}	-1.82	**2.79[b]**	-8.10	-1.98	0.24	**3.16[b]**
	{1,t}	-1.94	8.98	-10.62	-2.20	0.21	9.15
π	{1}	**-2.22[b]**	3.56	-7.00	-1.74	0.25	3.99
	{1,t}	-2.26	9.11	-9.45	-2.14	0.23	9.78
oil	{1}	0.15	24.26	0.19	0.11	0.55	22.89
	{1,t}	-2.69	6.22	-14.83	-2.71	0.183	6.23
hbm	{1}	-0.38	438.4	-1.62	-0.63	0.39	10.98
	{1,t}	-2.64	**3.86[a]**	**-24.68[a]**	**-3.49[a]**	**0.14[a]**	**3.86[a]**

[#]Variables are described in Appendix
[*]Critical values for the {1} case are from MacKinnon (1996) while the values for the {1,t} case are from ERS (1996), Table 1, p. 825.
[d]Critical values are based on ERS (1996), Table 1, p. 825.
[e]Critical values are based on Ng and Perron (2001).
[a, b,]Denote respectively significance values of 99, 95, and 90%.
Bold values indicate significance at 99 or 95%
[']Denotes deterministic trends where 1 and t denote a constant and time trend respectively.

Table 5.2
Residual Diagnostics w/in Regime[a]
Based on ADL Model

Regimes	Jarque-Bera $H_0\!:normality$	BG[b] $H_0\!:no\ ser.$ $correlation$	BPG $H_0\!:homo.$	ARCH[c] $H_0\!:no\ ARCH$
1959:01-2009:06	**80.75****	**16.1****	**69.17****	**18.54****
1959:01-1961:09	1.20	0.005	11.10	1.06
1961:10-1965:04	0.25	0.18	8.22	0.83
1965:05-1967:12	1.75	0.23	17.66	0.63
1968:01-1970:09	0.52	1.83	9.71	1.70
1970:10-1973:08	0.01	0.83	16.37	0.003
1973:09-1981:09	**20.89****	**10.42****	20.26	1.29
1981:10-1984:08	**11.66****	0.01	8.69	0.01
1984:09-1987:09	0.65	7.11	14.11	0.37
1987:10-1992:01	1.86	1.74	15.90	0.22
1992:02-1994:05	0.32	0.58	13.46	2.40
1994:06-1996:07	**8.39***	**7.00****	12.00	0.56
1996:08-1999:11	0.09	1.70	12.02	0.27
1999:12-2003:02	1.78	0.24	15.27	0.49
2003:03-2006:10	0.06	0.47	10.26	1.35
2006:11-2009:06	0.23	1.99	11.92	**3.29***

[a] BG denotes Breusch-Godfrey test for serial correlation. BPG denotes Breusch-Pagan-Godfrey test for
heteroskedasticity.
[b] Test statistics based on selecting 1 lag
[c] Test statistics based on selecting 1 lag
**,* denote significance at the 99 and 95% levels respectively

Table 5.3
EG and PO Cointegration Tests w/in Regime[*,#]

	Engle-Granger (1987)[a]			Phillips-Oliaris (1990)[b]		
	Lags[e]	Root	t-stat	Z-stat	Root[d]	t-stat	Z-stat
1959:01-1961:09	1	0.213	**-5.39** (0.07)	-25.17 (0.26)	0.02	**-5.33** (0.08)	**-31.43** (0.06)
1961:10-1965:04	0	0.78	-2.19 (0.98)	-9.18 (0.99)	0.77	-2.47 (0.96)	-11.91 (0.95)
1965:05-1967:12	0	0.49	-3.23 (0.78)	-15.97 (0.79)	0.50	-3.20 (0.79)	-15.63 (0.81)
1968:01-1970:09	1	0.042	**-5.27** (0.09)	**-76.14** (0.00)	0.43	-3.36 (0.73)	-18.22 (0.67)
1970:10-1973:08	0	0.48	-3.42 (0.71)	-17.68 (0.72)	0.47	-3.43 (0.70)	-17.98 (0.70)
1973:09-1981:09	0	0.82	-3.13 (0.81)	-16.88 (0.85)	0.83	-3.06 (0.83)	-16.08 (0.88)
1981:10-1984:08	0	0.48	-3.20 (0.79)	-17.73 (0.71)	0.52	-3.10 (0.83)	-16.44 (0.78)
1984:09-1987:09	7	-2.12	**-5.39** (0.08)	10.24 (0.99)	0.38	-3.91 (0.49)	-22.38 (0.45)
1987:10-1992:01	0	0.69	-3.15 (0.81)	-15.81 (0.85)	0.62	-3.39 (0.71)	-19.25 (0.70)
1992:02-1994:05	0	0.30	-3.75 (0.581)	-18.96 (0.57)	0.29	-3.75 (0.57)	-19.07 (0.56)
1994:06-1996:07	0	-0.11	-4.03 (0.46)	**-27.67** (0.08)	-0.07	-3.98 (0.49)	**-26.74** (0.10)
1996:08-1999:11	0	0.61	-3.01 (0.85)	-15.15 (0.86)	0.58	-3.11 (0.82)	-16.52 (0.80)
1999:12-2003:02	0	0.45	-3.73 (0.57)	-20.76 (0.56)	0.45	-3.74 (0.56)	-20.99 (0.55)
2003:03-2006:10	0	0.38	-4.51 (0.23)	-26.90 (0.27)	0.42	-4.44 (0.26)	-24.82 (0.37)
2006:11-2009:06	1	-0.15	-5.16 (0.11)	**-61.80** (0.00)	0.38	-4.21 (0.37)	-19.17 (0.60)

EG and PO denote Engle-Granger and Phillips-Ouliaris respectively. Bold values indicate rejection of the null at the 90% significance level, p-values in parentheses

*Tests based on a constant deterministic term.

[#]P-values for E-G and P-O are based on MacKinnon (1996) surface response simulations

[a]The null hypothesis is a unit root in the estimated residual

[b]The null hypothesis is a unit root in the estimated residual

[c]The null hypothesis is cointegration

[d]Based on the bias corrected autocorrelation coefficient

[e]Lag length selection based on SIC

Table 5.4
ECM Cointegration Test
Based on Banerjee _et al._ (1998)[#]

Regime	$\hat{\beta}^Y$ (se)
1959:01-1961:09	-.718* (.165)
1961:10-1965:04	-.622* (.105)
1965:05-1967:12	-.514 (.181)
1968:01-1970:09	-.371 (.315)
1970:10-1973:08	-1.01* (.174)
1973:09-1981:09	-.250 (.074)
1981:10-1984:08	-.254 (.498)
1984:09-1987:09	-.403 (.226)
1987:10-1992:01	-.274 (.090)
1992:02-1994:05	-.123 (.618)
1994:06-1996:07	-1.67 (2.02)
1996:08-1999:11	-.544* (.102)
1999:12-2003:02	-.627* (.131)
2003:03-2006:10	-.673 (.178)
2006:11-2009:06	-.734 (.351)

[#]Critical values based on Banerjee _et al._ (1998, p. 276) Table 1. Values for six regressors were calculated by extrapolation. Coefficients are reported with standard errors in parentheses.
*denotes significance at the 99% level

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Table 5.5: Error Correction Model within Regime*

Variable	Model5961	Model6165	Model6870	Model7073	Model8487	Model9496	Model9699	Model9903	Model0609
Dsp500_1	-0 085	0 120	**0.261**	**0.353**	0 044	0 181	-0 138	-0 054	0 055
Dearnings	**-3.010**	**-2.472**	-3 638	**-2.821**	**-1.330**	-0 488	-1 481	**-2.232**	**-0.184**
Dearnings_	-0 510	1 554	**-7.760**	-0 762	0 400	-0 639	-0 140	-0 025	0 110
Dip	0 171	0 087	-0 399	**1.392**	-1 075	-0 277	-1 087	**4.261**	0 295
Dip_1	**0.608**	0 049	1 511	**-0.857**	**-3.585**	0 010	**-1.507**	1 714	**1.312**
Dtbill	-0 002	0 006	**-0.066**	0 007	-0 022	-0 034	0 039	0 025	**0.044**
Dtbill_1	0 008	-0 025	0 002	**0.017**	-0 003	0 014	-0 017	-0 002	-0 022
Dinf	**-0.025**	0 021	**-0.010**	0 008	**0.069**	0 005	0 038	0 017	**0.051**
Dinf_1	0 011	-0 011	**0.114**	**0.021**	**-0.047**	**-0.084**	-0 006	-0 018	0 016
Doil	**3.214**	**7.231**	**0.466**	-0 047	-0 143	-0 041	-0 030	-0 034	**-0.129**
Doil_1	-0 056	0 381	0 901	-0 274	0 038	**0.096**	-0 011	-0 013	-0 149
Dhbm	**173.963**	**294.076**	**194.365**	**336.600**	**182.737**	82 014	**138.501**	**273.260**	**96.340**
Dhbm_1	**-157.415**	**-234.268**	**-90.788**	**-223.398**	**-178.019**	-8 333	-51 317	**-274.572**	23 951
e5961_1	**-0.719**								
e6165_1		**-0.373**							
e6870_1			**-0.373**						
e7073_1				**-1.011**					
e8487_1					**-0.403**				
e9496_1						**-1.649**			
e9699_1							**-0.319**		
e9903_1								**-0.059**	
e0609_1									**-0.734**
adj R²	0 947	0 808	0 702	0 932	0 475	0 766	0 697	0 822	0 887
F	**39.180**	**13.657**	**5.87**	**34.352**	**3.330**	**6.842**	**6.90**	**13.532**	**18.357**

*Coefficients reported, bold stats denote 95% sig , standard errors omitted for brevity, e denotes resid , _1 denotes lag, D denotes 1st difference

Table 5.6
Residual Diagnostics from ECM Equation (6)

		BG Test		Normality Tests			
	Lags	Chi^2	p-value	Pr(skew)	Pr(kurt)	Chi^2	p-value
1959 01-1961 09	1	2 06	0 153	0 769	0 347	1 034	0 597
	2	3 09	0 212				
1961 10-1965 04	1	0 001	0 949	0 651	0 912	0 223	0 897
	2	**12.25**	0 002				
1968 01-1970 09	1	0 065	0 800	0 441	0 421	1 320	0 516
	2	3 058	0 217				
1970 10-1973 08	1	**10.28**	0 001	0 255	0 619	1 253	0 439
	2	**24.31**	0 000				
1984 09-1987 09	1	**3.078**	0 082	0 818	0 725	0 183	0 915
	2	3 078	0 213				
1994 06-1996 07	1	**20.25**	0 000	0 848	0 247	1 500	0 474
	2	**20.26**	0 000				
1996 08-1999 11	1	1 178	0 277	0 701	0 056	4 01	0 1343
	2	10 032	0 007				
1999 12-2003 02	1	0 292	0 588	0 725	0 811	0 18	0 913
	2	0 890	0 641				
2006 10-2009 06	1	**6.59**	0 012	0 645	0 828	0 260	0 878
	2	**7.75**	0 024				

Notes: BG denotes Breusch-Godfrey residual serial correlation test with a null of no serial correlation The normality tests have a null hypothesis of normality Bold values denote rejection of the null at the 95% significance level

Table 5.7
Out-of-Sample Fit
Root Mean Square Forecast Errors and Direction of Change Statistics (DCS)[a]

Regime	Horizon[c]	RW	RW w/ Drift	FR[d] (2010)	ECM[b]	DCS	Obs.
1959:01-1961:09	1	2.81	2.69	7.43	2.97	62	13
	3	7.14	6.78	11.51	**5.39**	82***	11
1961:10-1965:04	1	1.97	1.83	8.17	2.77	78**	23
	3	3.69	2.91	11.69	**3.33**	95***	21
	6	7.01	5.39	19.16	**4.15**	100***	18
	12	14.09	11.34	44.18	**5.68**	100***	12
1965:05-1967:12	1	2.51	2.68	6.24	3.79	42	12
	3	5.53	6.19	13.75	**2.41**	80***	10
1968:01-1970:09	1	4.24	4.28	6.42	4.76	62	13
	3	8.26	8.19	9.56	**5.42**	91***	11
1970:10-1973:08	1	2.21	2.55	7.03	3.29	40	15
	3	4.68	6.22	10.81	**4.60**	69**	13
	6	7.26	10.88	15.97	**6.04**	40	10
1973:09-1981:09	1	3.39	3.49	12.71	4.96	55	77
	3	6.17	6.63	16.84	7.74	79***	75
	6	8.21	9.16	23.46	14.33	79***	72
	12	12.32	15.03	38.35	**9.75**	89***	66
	24	16.15	22.02	56.70	**5.13**	91***	54
1973:03-1981:06[e]	1	-	-	13.07	-	-	-
	3	-	-	14.87	-	-	-
	6	-	-	18.22	-	-	-
	12	-	-	26.29	-	-	-
	24	-	-	47.95	-	-	-
1973:09-1981:06[f]	1	-	-	11.02	-	-	-
	3	-	-	12.66	-	-	-
	6	-	-	15.59	-	-	-
	12	-	-	22.41	-	-	-
	24	-	-	38.16	-	-	-
1981:10-1984:08	1	3.09	3.18	14.36	**3.04**	40	15
	3	4.06	5.69	29.18	**3.14**	69**	13
	6	5.84	11.32	62.47	**3.58**	80***	10
1984:09-1987:09	1	3.55	3.03	22.76	4.27	59	17
	3	7.86	5.61	25.93	**4.84**	80***	15
	6	13.23	7.87	30.69	**6.07**	92***	12
1987:10-1992:01	1	3.50	3.51	9.50	**3.24**	63*	32
	3	7.31	7.51	11.74	**3.51**	80***	30
	6	9.96	10.42	13.43	**3.57**	85***	27
	12	13.10	13.84	13.59	**4.95**	95***	21

Table 5.7 Continued

1996:08- 1999:11	1	4.39	4.16	14.24	**3.84**	75***	20
	3	8.47	8.23	24.68	**4.52**	67**	18
	6	12.07	11.35	40.67	**3.69**	93***	15
1999:12- 2003:02	1	5.09	4.88	11.68	**6.75**	47	19
	3	9.95	9.21	13.80	**11.16**	59	17
	6	14.71	12.25	16.98	17.33	36	14
2003:03- 2006:10	1	2.10	1.98	2.29	2.44	67**	24
	3	3.97	3.80	2.79	**3.04**	77***	22
	6	4.48	5.37	2.60	**3.04**	74**	19
	12	8.08	9.83	3.17	**3.77**	92***	13

[a] Root Mean Square Errors are in percentage terms. DCS figures denote the percentage of correct predictions based on the ECM model. All figures are based on an 18-month estimation period. RW denotes the random walk model. ECM denotes error correction model. Excluded regimes are due to insufficient observations.

[b] The error correction model is based on the long-run residuals generated by the ADL(2,2;6) model.

*,**,*** denote significance based on the binomial distribution at the 90, 95 and 99% levels respectively.

Bold values indicate that the ECM model outperforms either the RW or RW w/ Drift models.

[c] Denotes the number of months ahead of the rolling estimation window.

[d] The Gordon-Earnings model is generated using a 3-month foreward-looking growth rate of earnings as in FR (2010). These statistics are roughly equal to those generated by FR (2010); even though the data source of earnings is the same FR (2010) generate earnings from backing them out of the price-to-earnings ratio whereas I collect the earnings data directly from the data source. See www.robertshiller.com.

[e] This is the original MR sample period that FR (2010) estimate for the Gordon-earnings model without accounting for temporal instability.

[f] This is the FR (2010) Gordon-earnings model tested over the original MR sample but accounting for the breakpoint that I found in Chapter 3 at 1973:08. As such, the procedure begins on 1973:09.

Figure 1.1
S&P500 Price-to-Earnings Ratio and BM
Sample Period: 1881:01-2001:05
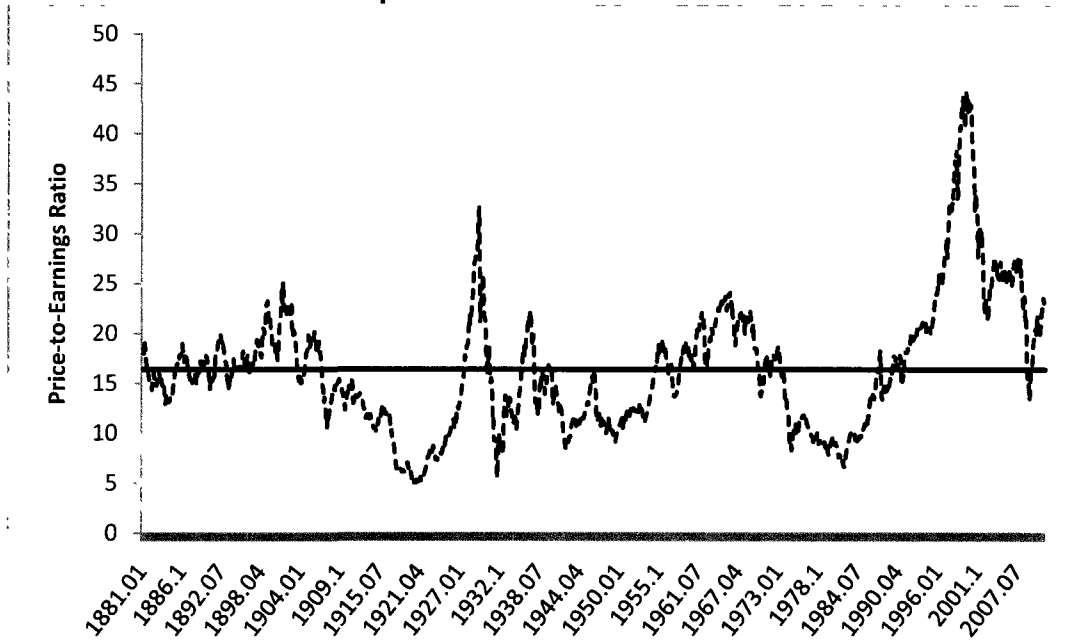
Notes: BM is benchmark. The dotted line denotes the S&P500 price relative to a 10-year trailing average of earnings. The solid line denotes the historical benchmark level which, here, is equal to the historical average of 16.4. Data are taken from Shiller (2000b) which are updated at his website.

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Figure 1.2
S&P500 Dividend-Price Ratio and BM
Sample Period: 1860-2000
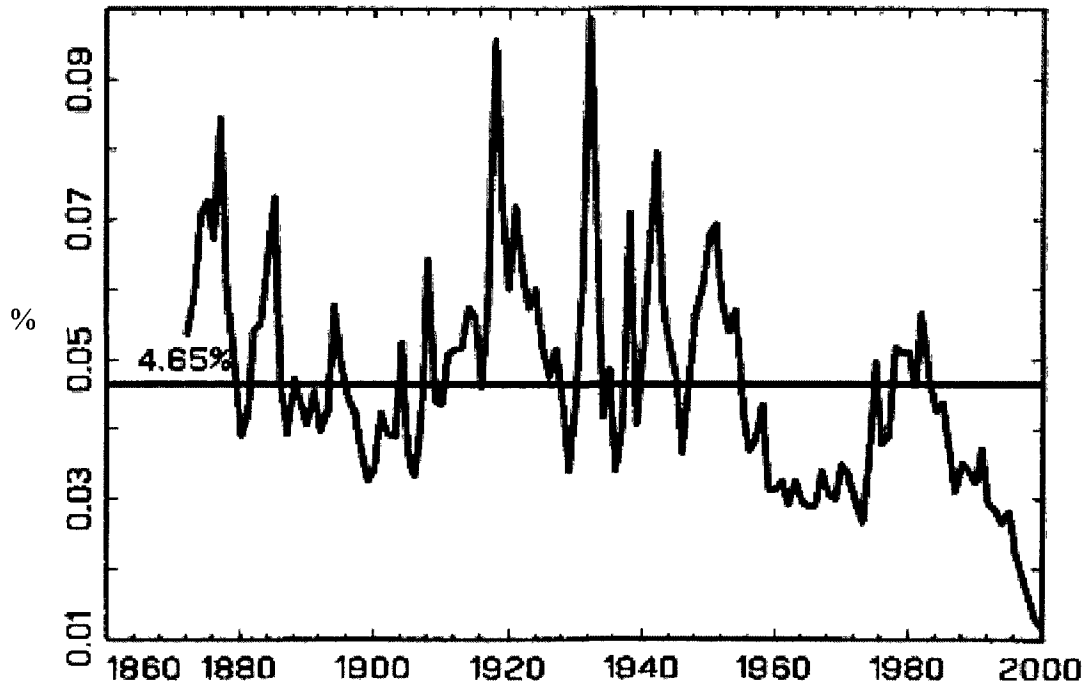
Notes: BM is benchmark. The highly variable line denotes the dividend-price ratio for the S&P500. The horizontal line captures the benchmark level and is generated by a historical average of the dividend-price series which equals 4.65%. The Figure is taken from Campbell and Shiller (2001, Table 4).

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Figure 3.1
Psychological Considerations
Sample Period: 1993:01-2009:12
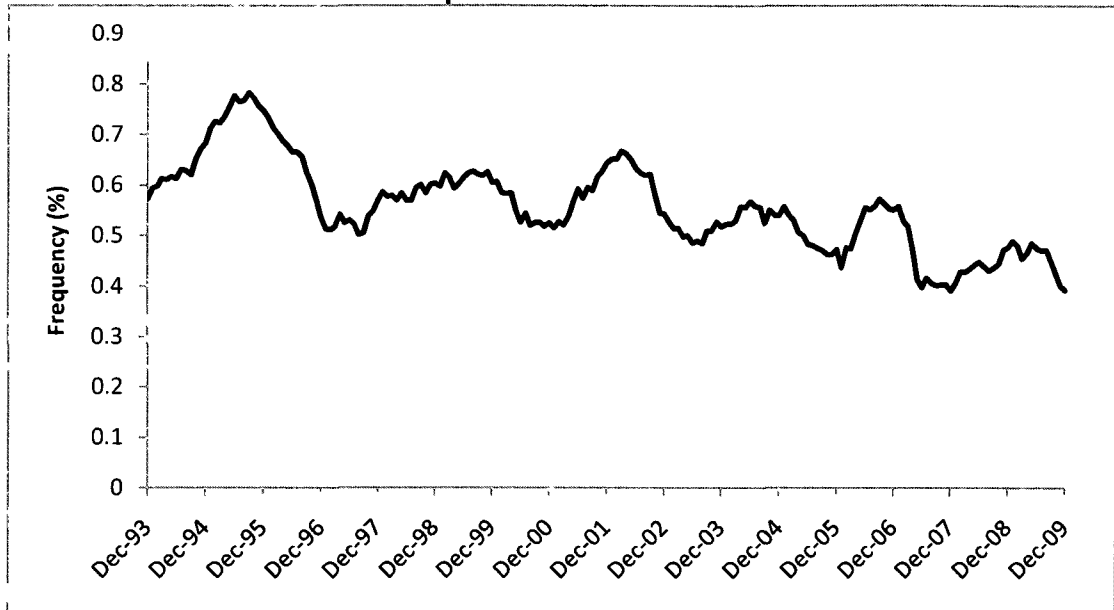
Notes: Average monthly frequency of mentions in wrap reports: Psychological considerations.

Figure 3.2
Pure Psychological Considerations
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
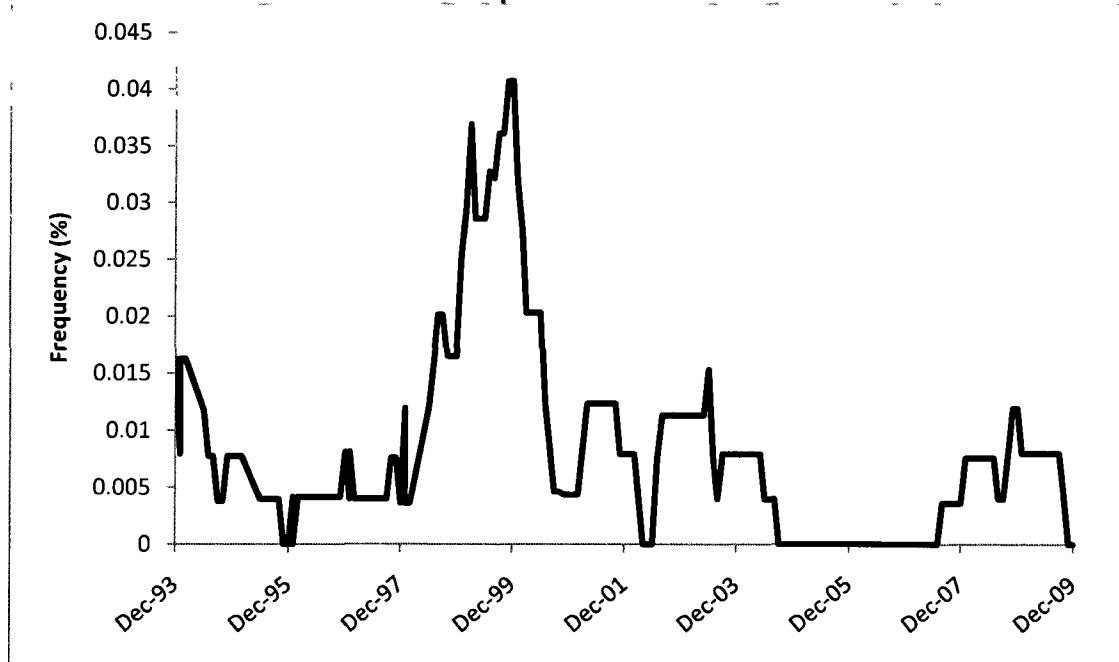
Notes: Average monthly frequency of mentions in wrap reports: Pure psychological consideration

Figure 3.3
Technical Momentum-Related Considerations
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
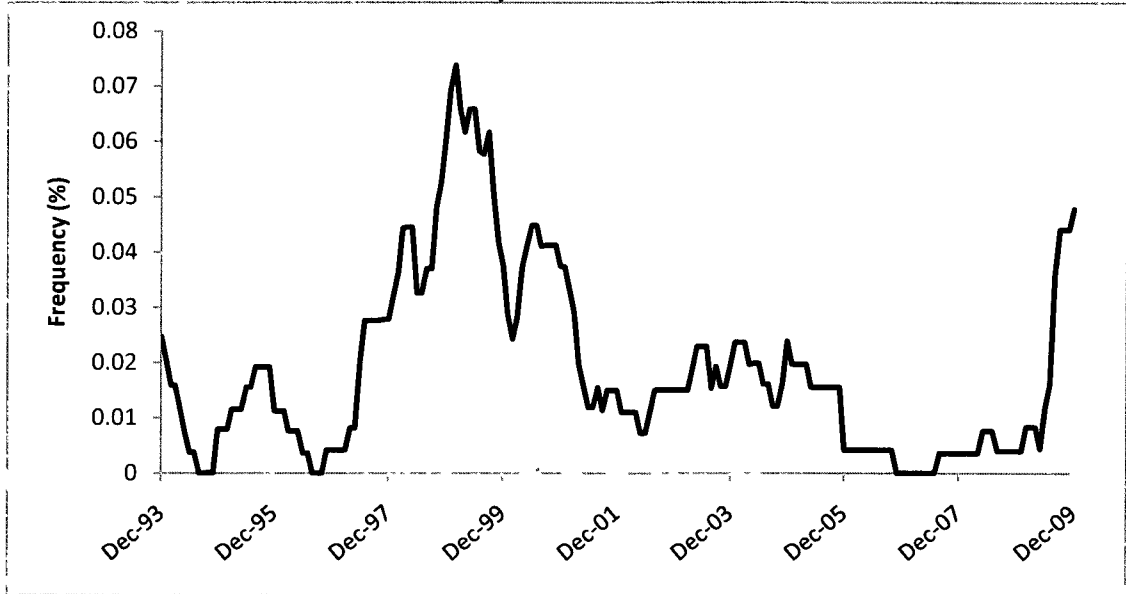
Notes: Average monthly frequency of mentions in wrap reports: Technical momentum-related considerations.

Figure 3.4
Technical Non-Momentum-Related Considerations
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
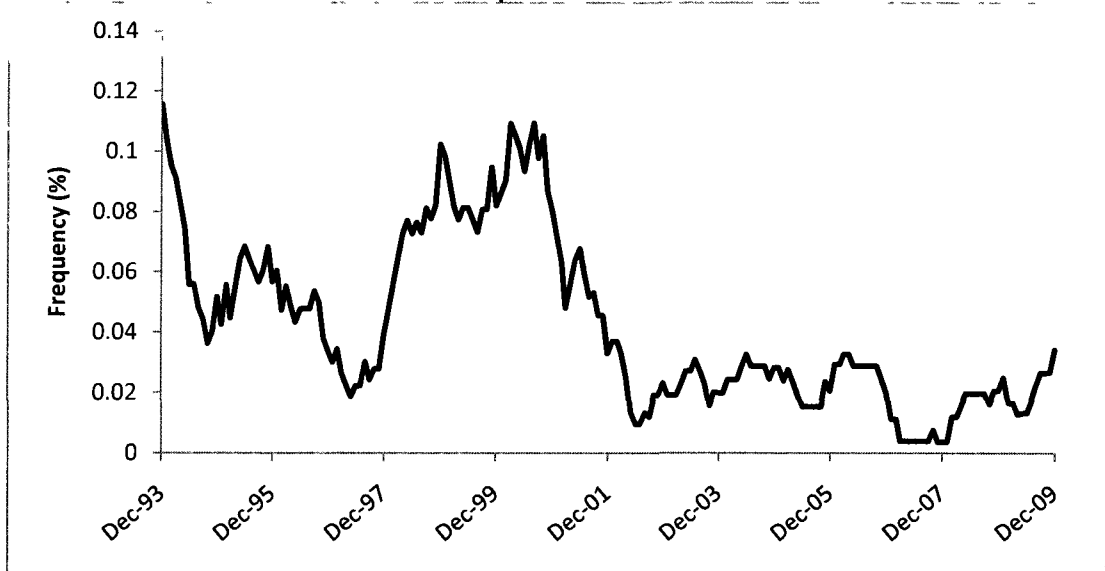
Notes: Average monthly frequency of mentions in wrap reports: Technical non-momentum-related considerations

Figure 3.5
Bubble Considerations
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
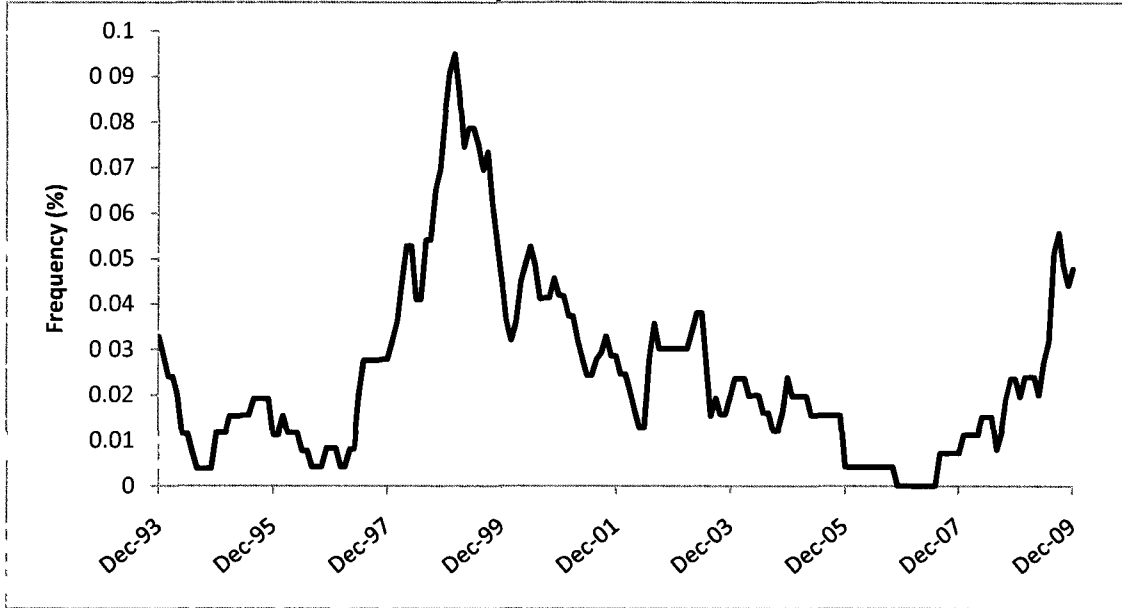
Notes: Average monthly frequency of mentions in wrap reports: Bubble considerations.

Figure 3.6
Disaggregated Fundamental Considerations
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
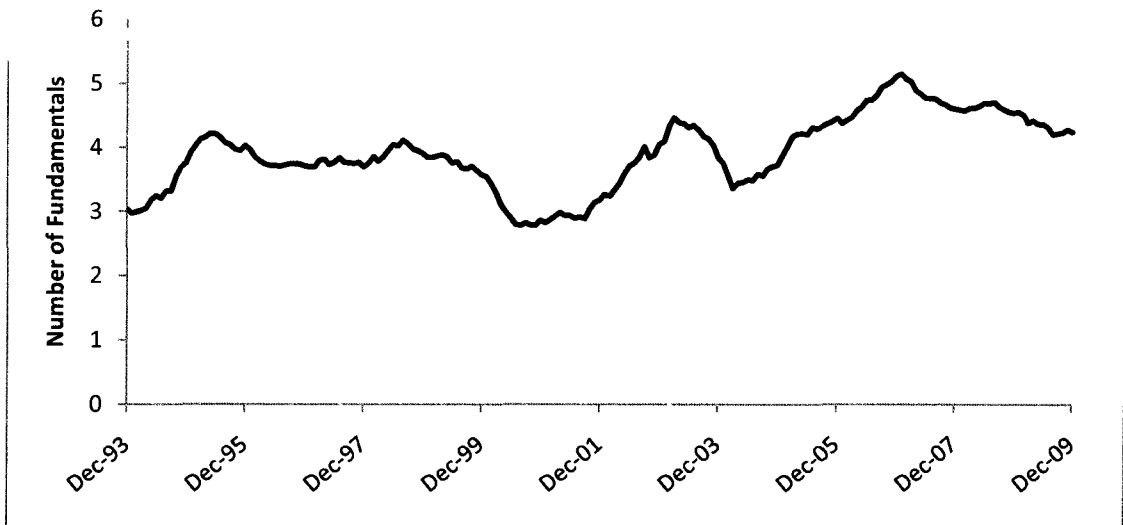
Notes: Average monthly frequency of mentions in wrap reports Number of fundamentals

Figure 3.7
Earnings
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
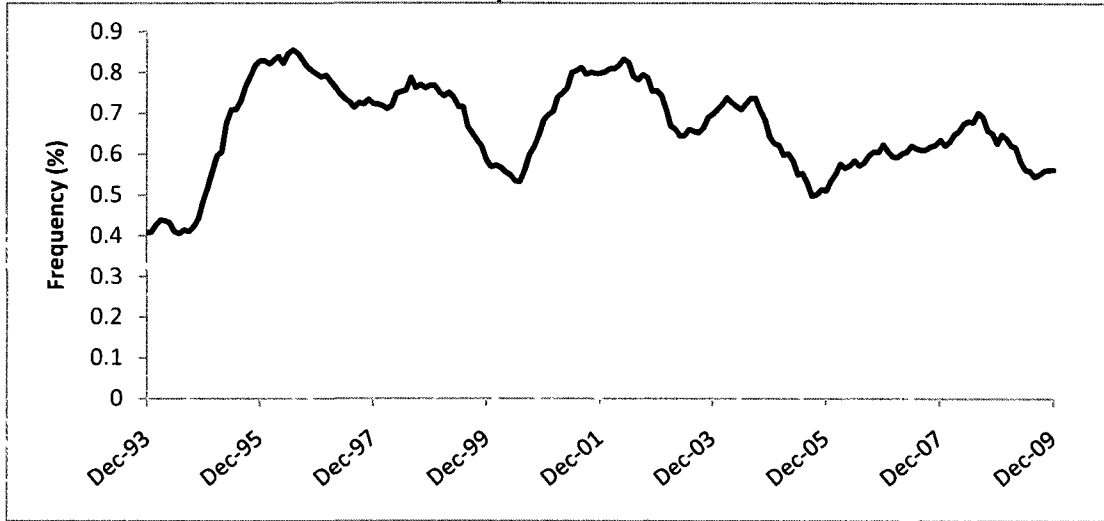
Notes: Average monthly frequency of mentions in wrap reports: Earnings

Figure 3.8
Oil Prices
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
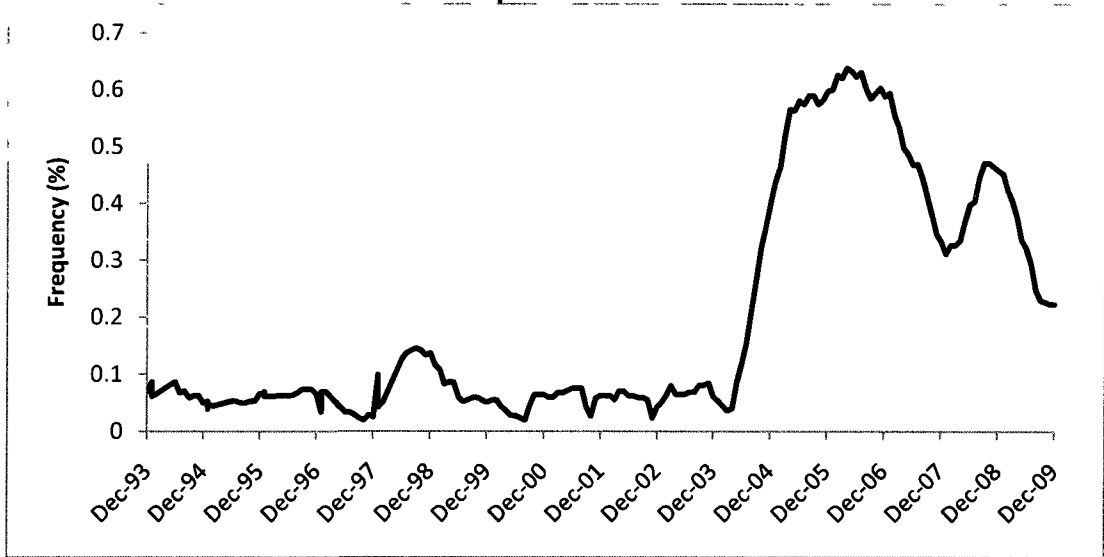
Notes: Average monthly frequency of mentions in wrap reports: Oil Prices

Figure 3.9
Interest Rates
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
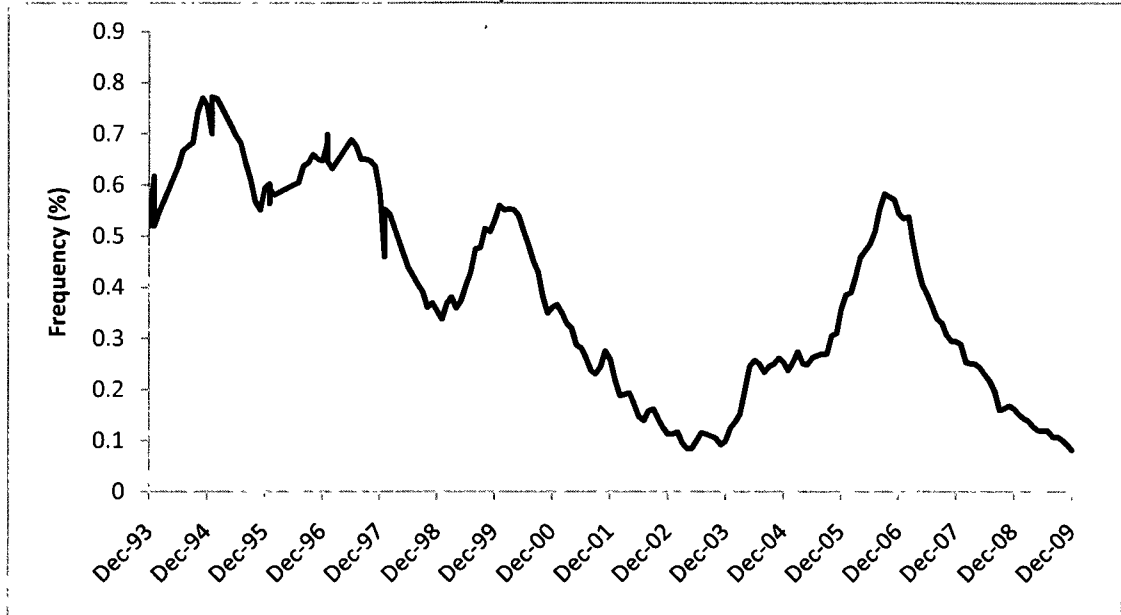
Notes: Average monthly frequency of mentions in wrap reports: Interest Rates

Figure 3.10
Inflation
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
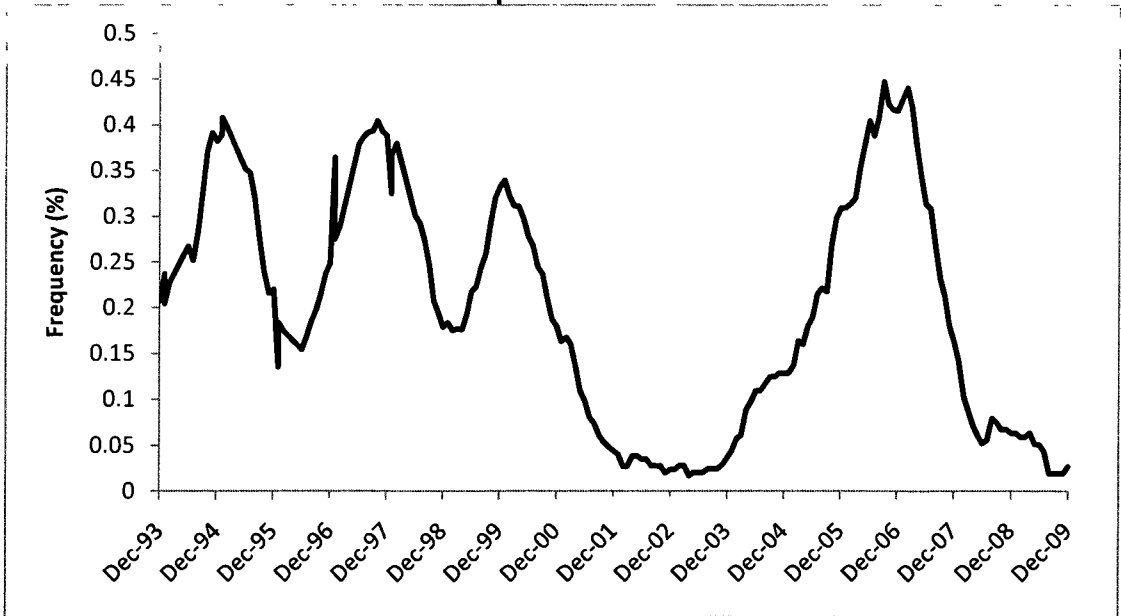
Notes: Average monthly frequency of mentions in wrap reports: Inflation

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Figure 3.11
Price Gap
Based on *Bloomberg News'* Market Wraps
Sample: 1993:01-2009:12
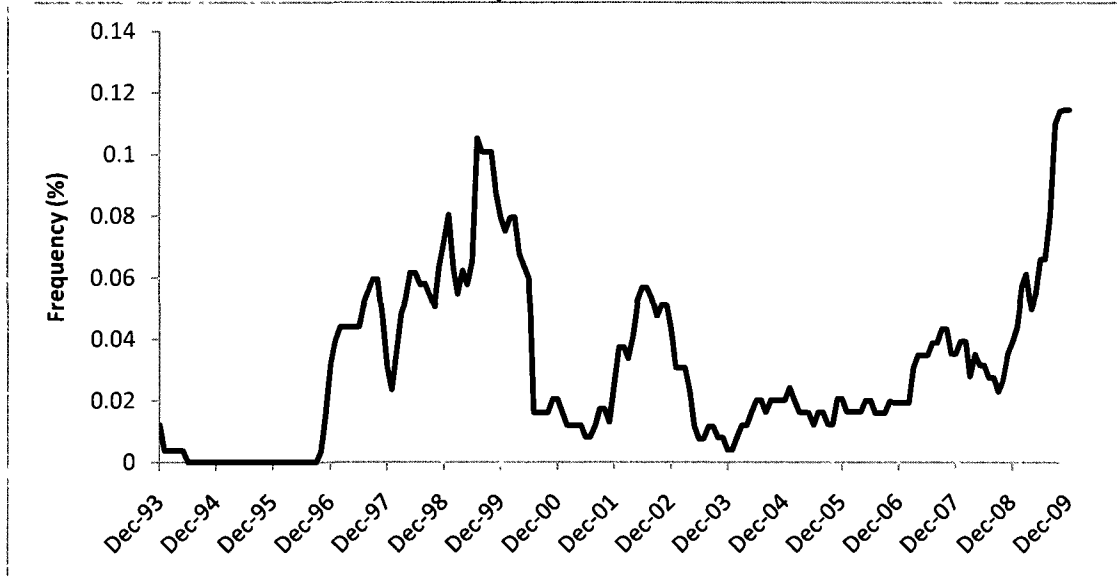
Notes: Average monthly frequency of mentions in wrap reports: Price gap.

Figure 3.12
Economy: Directional Sign Change
Based on *Bloomberg News'* Market Wraps
Sample Period: 1993:01-2009:12
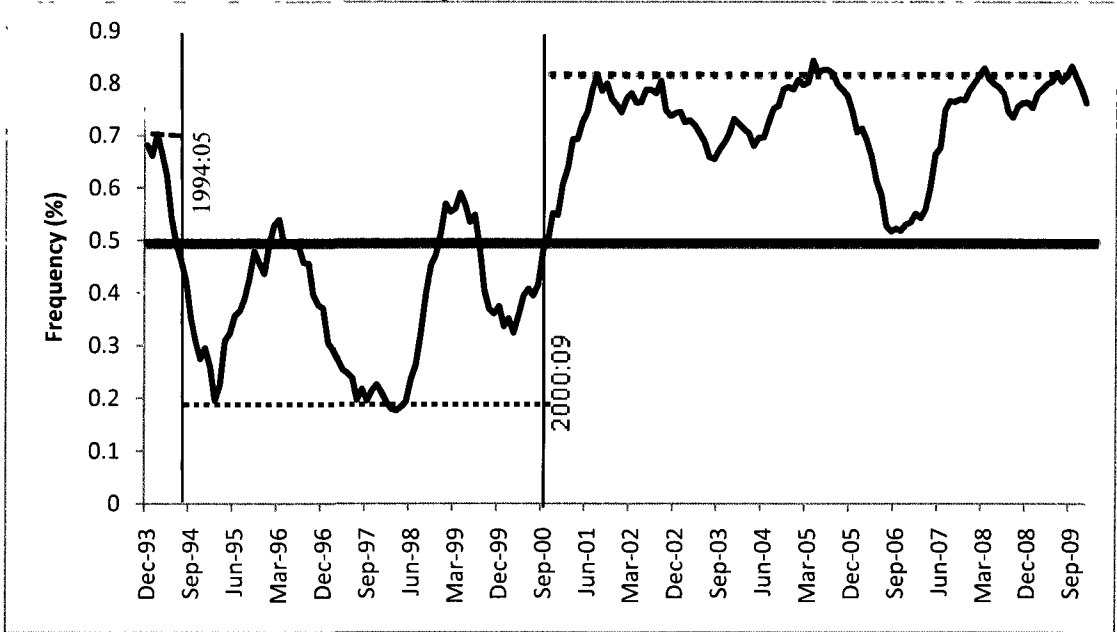
Notes: This figure plots the proportion of days that the economy shared a positive sign with stock prices over the period. Periods are identified where this frequency intersects the 50% line and maintains its new directional relation to the market.

Figure 3.13
Oil Prices: Directional Sign Change
Based on *Bloomberg News'* Market Wraps
Sample Period: 1993:01-2009:12
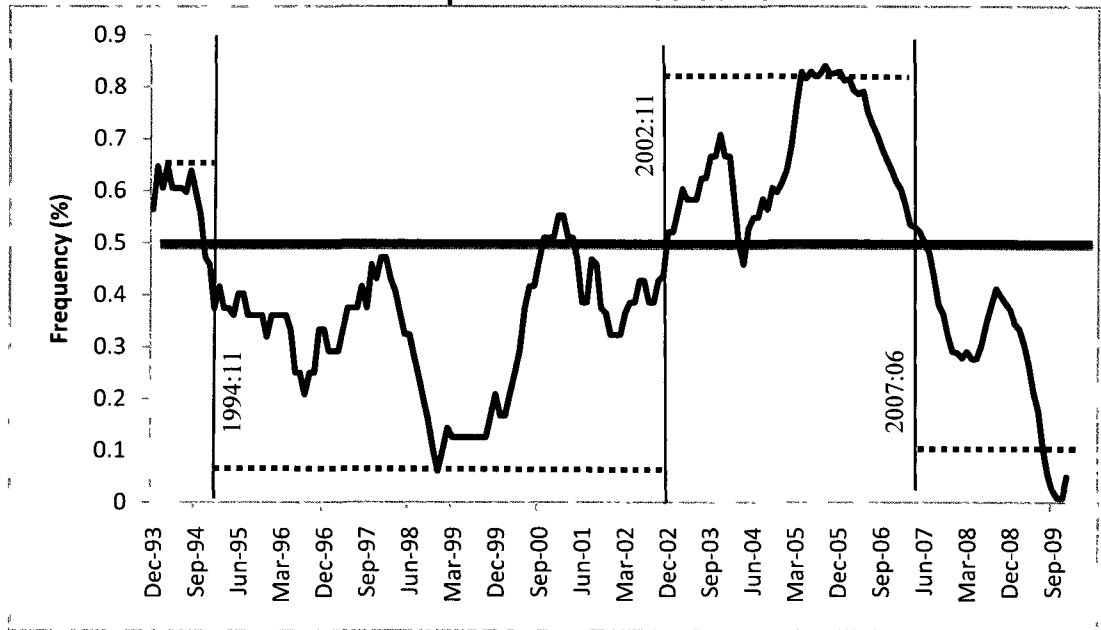
Notes: This figure plots the proportion of days for which oil prices shared a negative with stock prices sign over the period. Periods are identified where this frequency intersects the 50% line and maintains its new directional relation to the market

Figure 3.14
Directional Sign Change: Economy and Oil Prices
Based on *Bloomberg News'* Market Wraps
Sample Period: 1993:01-2009:12
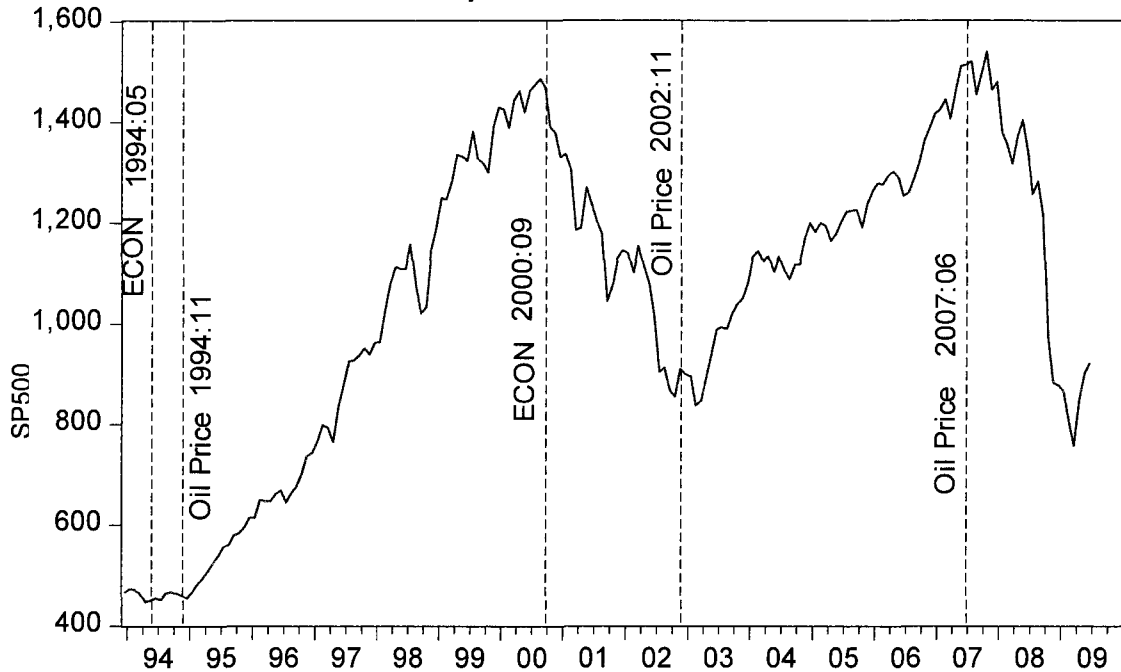
Notes: This figure plots the periods for which the economy and oil prices underwent a directional sign change with the stock market and maintained such change. The time series is the S&P 500 Composite Index price plotted on the vertical axis.

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Figure 4.1
Graphs of Data

lnS&P 500

lnSP500

70
65
60
55
50
45
40

1960 1965 1970 1975 1980 1985 1990 1995 2000 2005 2010

lnEarnings

lnEarnings

45
40
35
30
25
20
15

1960 1965 1970 1975 1980 1985 1990 1995 2000 2005 2010

lnIndustrial Production

lnIP

450
425
400
375
350
325

1960 1965 1970 1975 1980 1985 1990 1995 2000 2005 2010

lnT-Bill

tbll

150
175
100
75
50
25

1960 1965 1970 1975 1980 1985 1990 1995 2000 2005 2010

Inflation

inf

15
10
05
00
-05
10
15

1960 1965 1970 1975 1980 1985 1990 1995 2000 2005 2010

lnOil

lnOil

60
55
50
45
40
35
30

1960 1965 1970 1975 1980 1985 1990 1995 2000 2005 2010

186

lnBM

Notes: The S&P500, Earnings, Industrial Production, Oil Prices and the Benchmark are all expressed in logarithmic form. Interest rates and the inflation rate are expressed in percent form and, as such, are not in logarithmic form.

Figure 4.2
CUSUMSQ and 1-Step Chow Test
Sample: 1959:03-1964:02
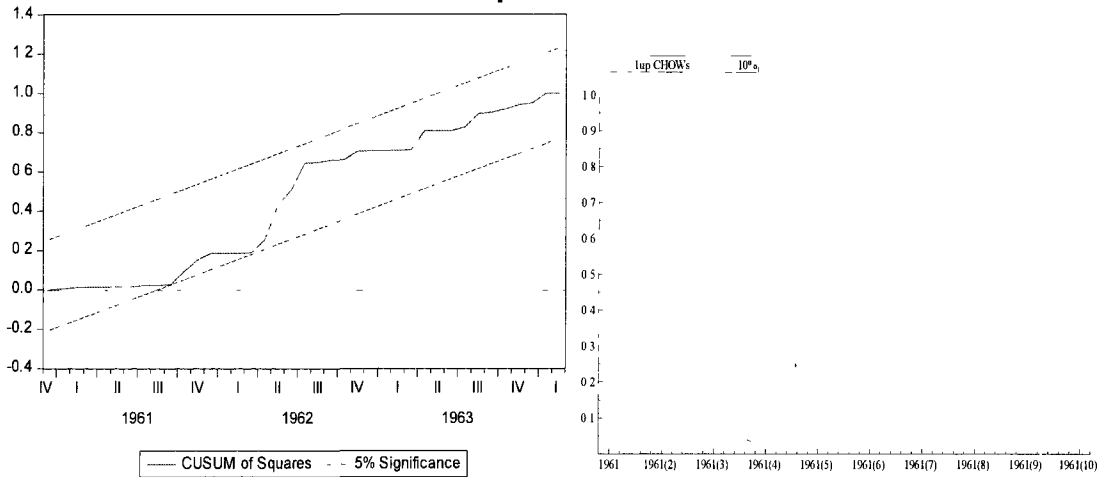
Figure 4.3
CUSUMSQ and 1-Step Chow Test
Sample: 1961:12-1966:11

CUSUM of Squares   5% Significance
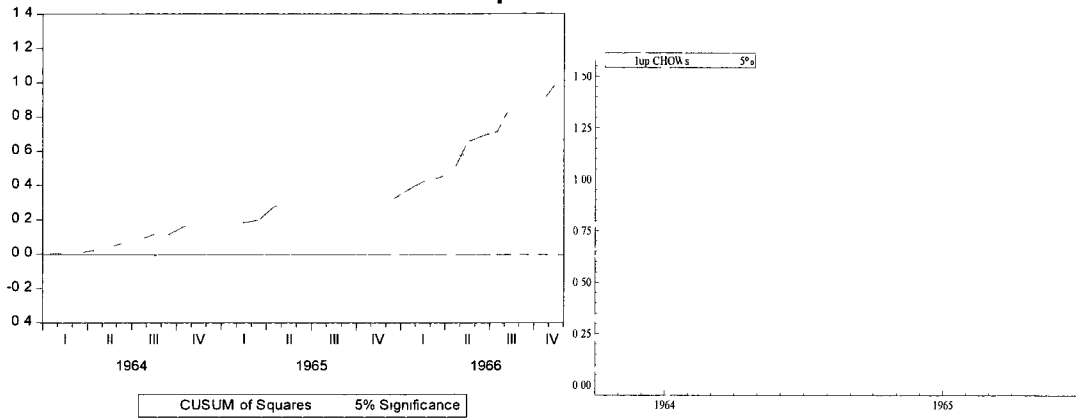
Figure 4.4
CUSUMSQ and 1-Step Chow Test
Sample: 1965:07-1970:06

CUSUM of Squares   5% Significance
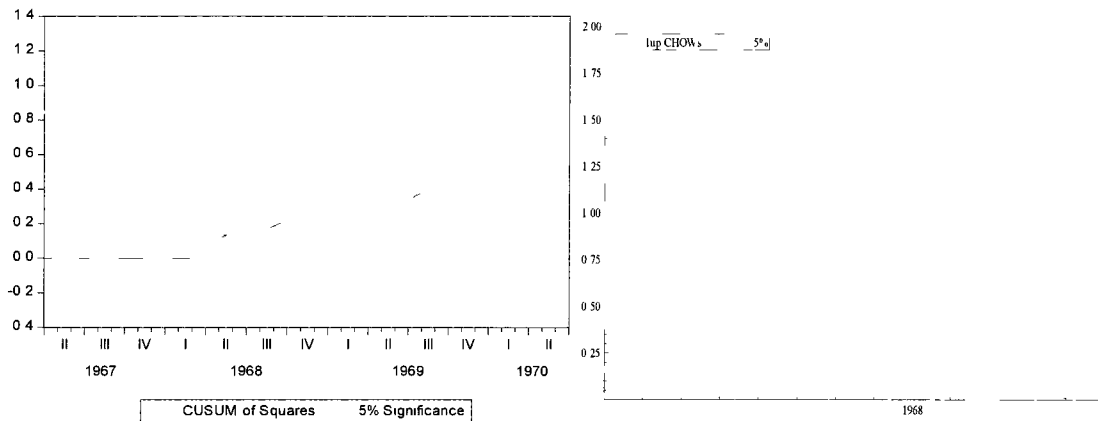
Figure 4.5
CUSUMSQ and 1-Step Chow Test
Sample: 1968:03-1978:02

CUSUM of Squares   5% Significance
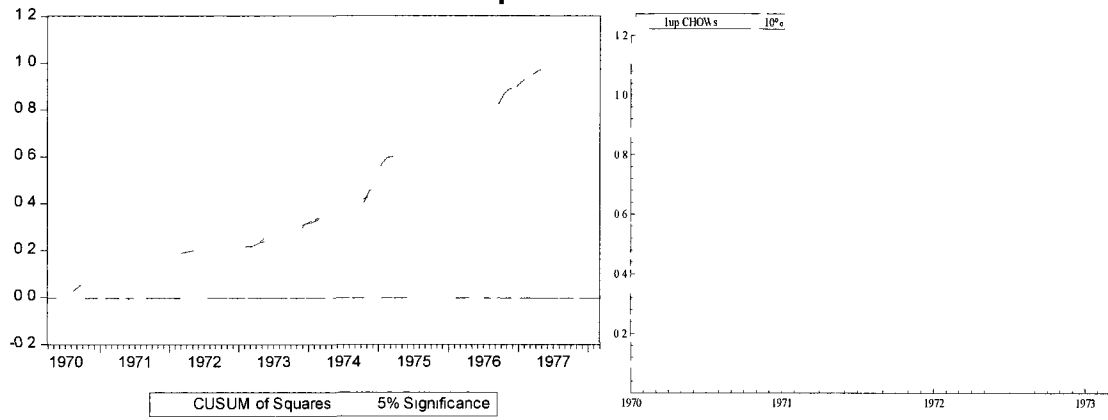
Figure 4.6
CUSUMSQ and 1-Step Chow Test
Sample: 1970:12-1975:11

CUSUM of Squares   5% Significance

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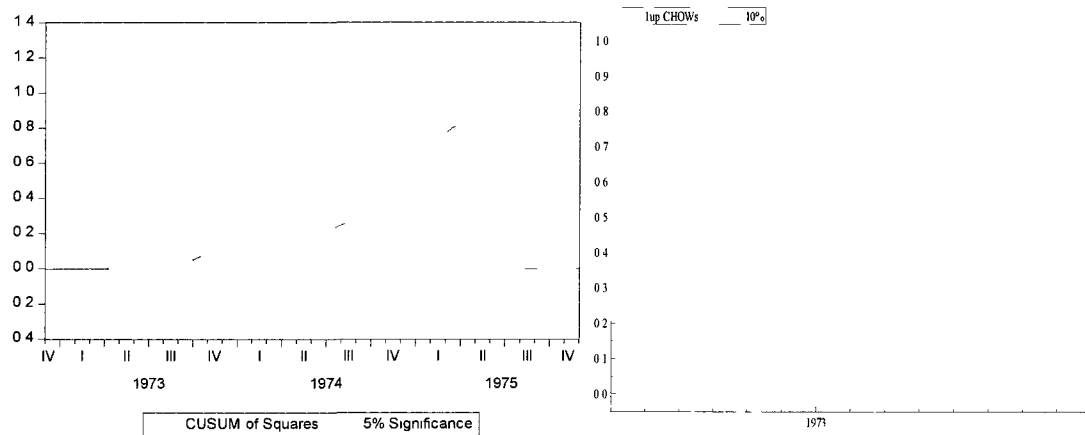
Figure 4.7
CUSUMSQ and 1-Step Chow Test
Sample: 1978:11-1982:10

CUSUM of Squares   5% Significance
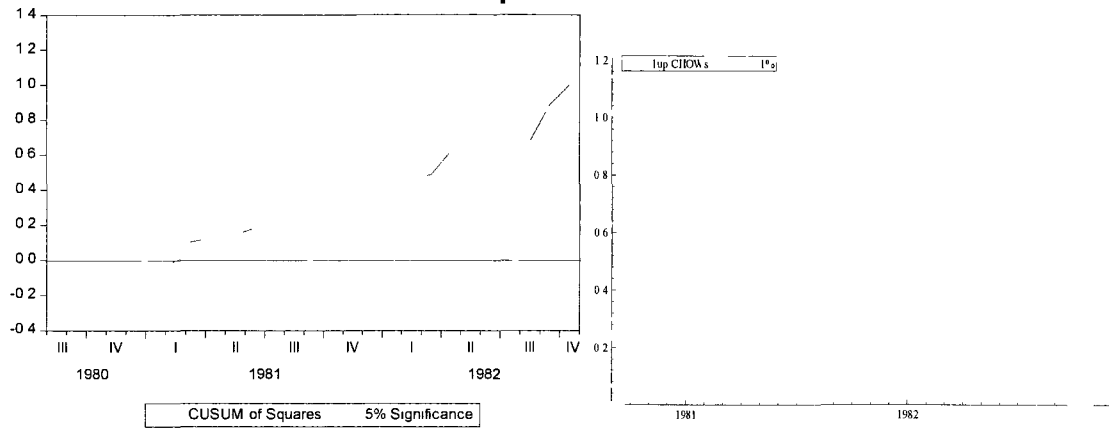
Figure 4.8
CUSUMSQ and 1-Step Chow Test
Sample: 1981:12-1996:11

CUSUM of Squares   5% Significance
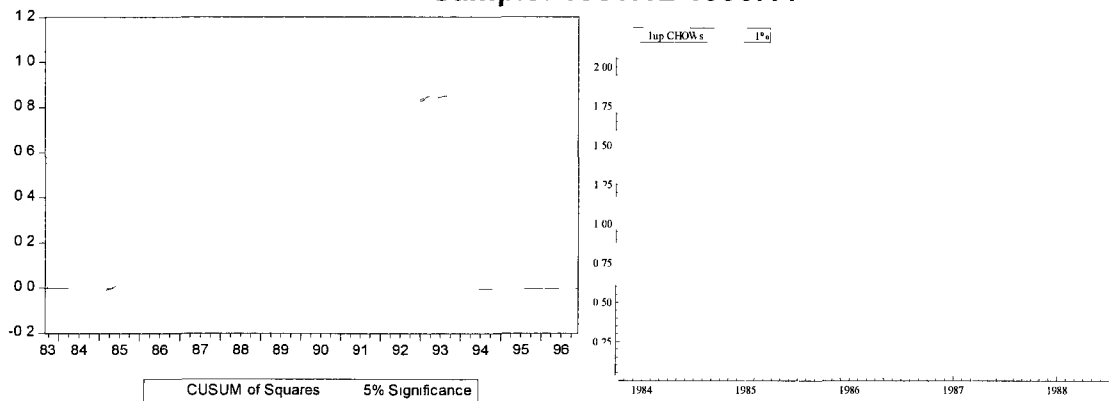
Figure 4.9
CUSUMSQ and 1-Step Chow Test
Sample: 1984:11-1994:10

CUSUM of Squares   5% Significance
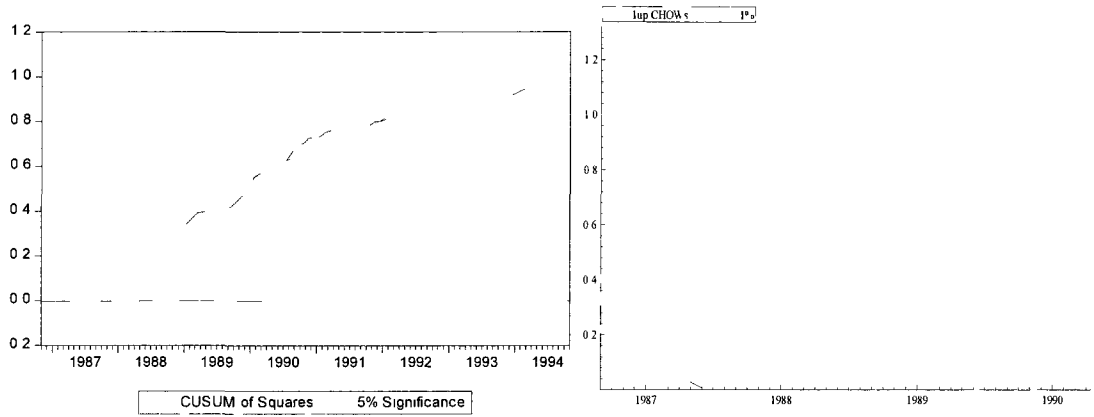
Figure 4.10
CUSUMSQ and 1-Step Chow Test
Sample: 1987:12-1997:11

CUSUM of Squares   5% Significance

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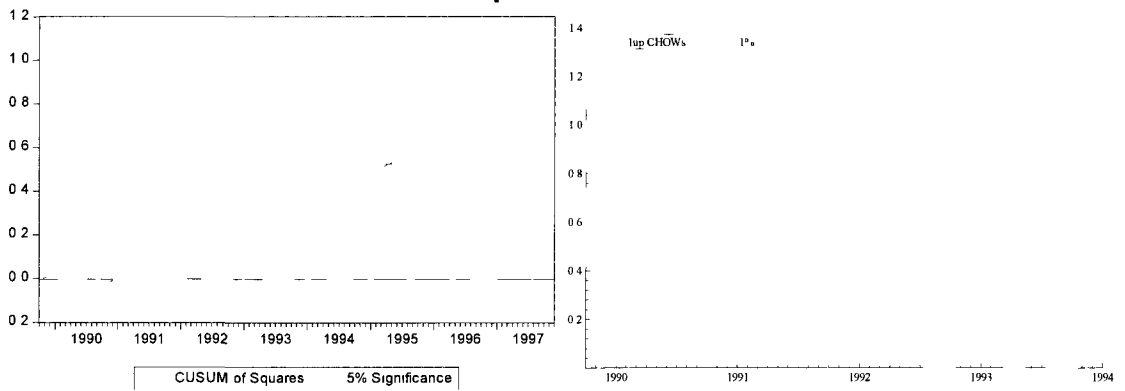
Figure 4.11
CUSUMSQ and 1-Step Chow Test
Sample: 1992:04-1997:03
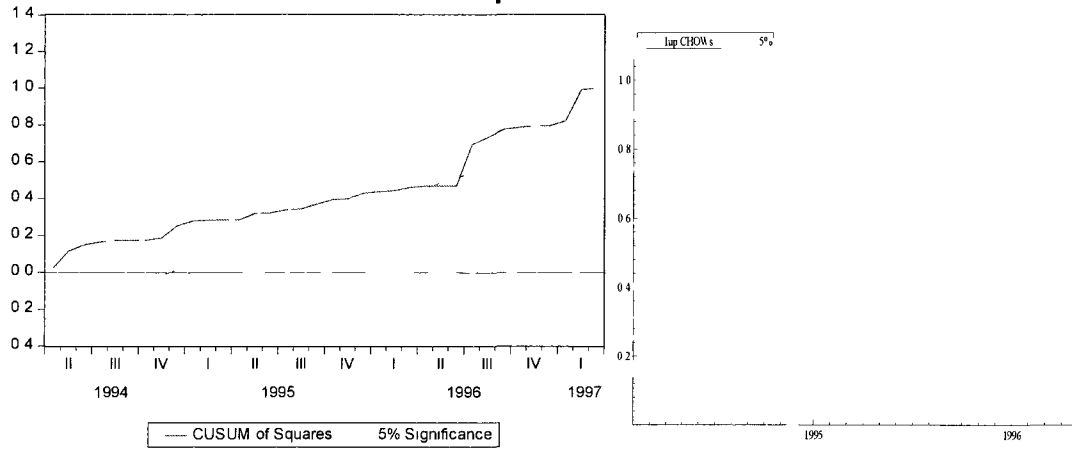
Figure 4.12
CUSUMSQ and 1-Step Chow Test
Sample: 1994:08-2003:07
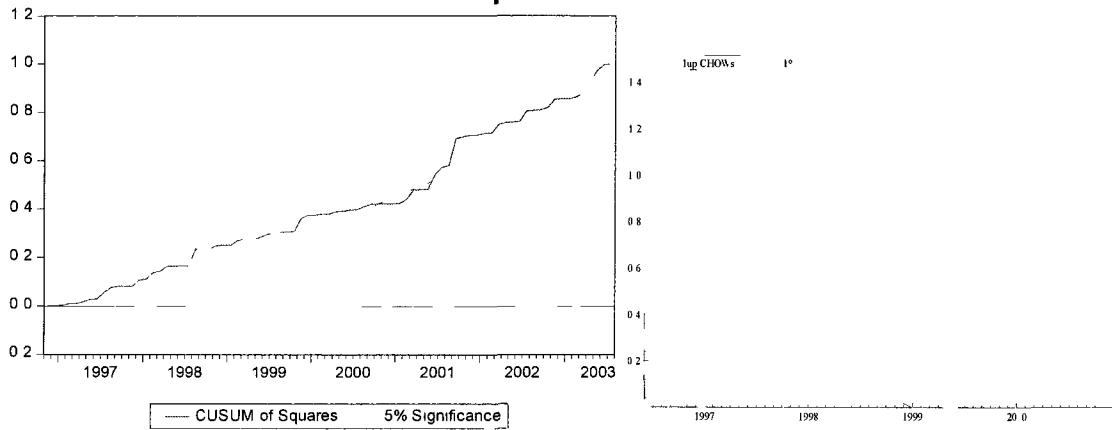
Figure 4.13
CUSUMSQ and 1-Step Chow Test
Sample: 1996:10-2009:06

CUSUM of Squares   5% Significance

1up CHOWs   1%
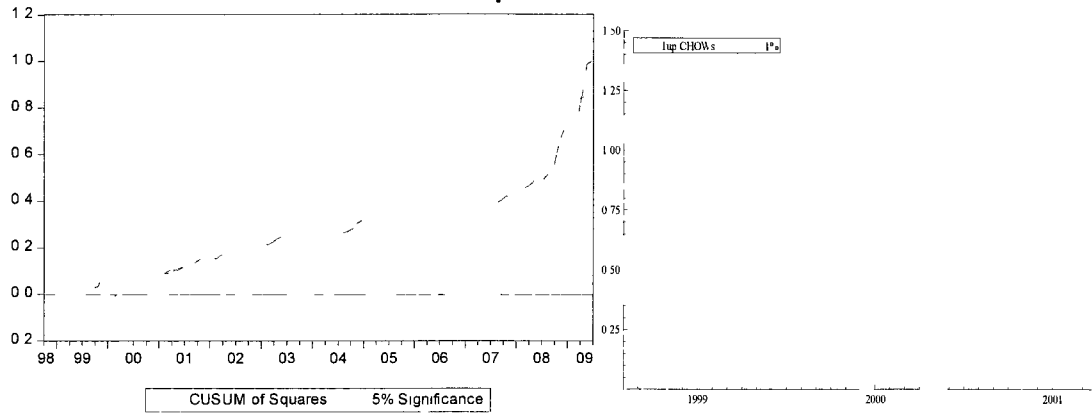
Figure 4.14
CUSUMSQ and 1-Step Chow Test
Sample: 2000:02-2009:06

CUSUM of Squares   5% Significance

1up CHOWs   10%

193
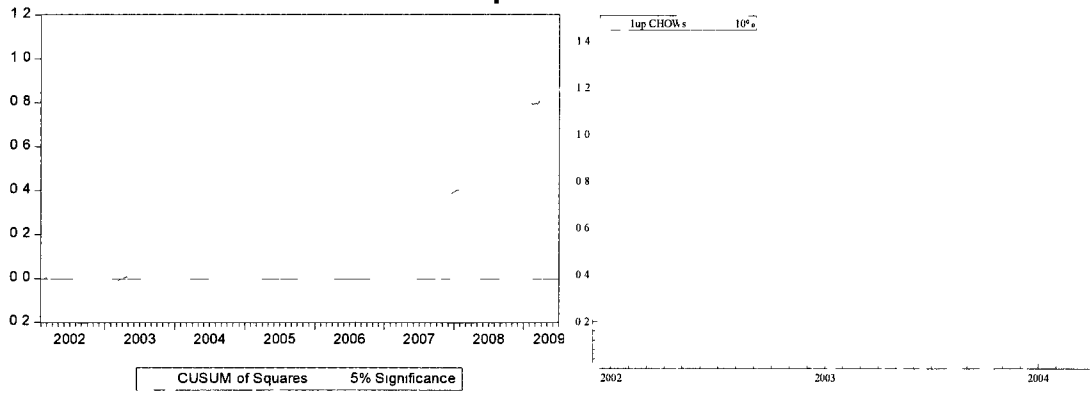
Figure 4.15
CUSUMSQ and 1-Step Chow Test
Sample: 2003:05-2009:06

CUSUM of Squares   5% Significance
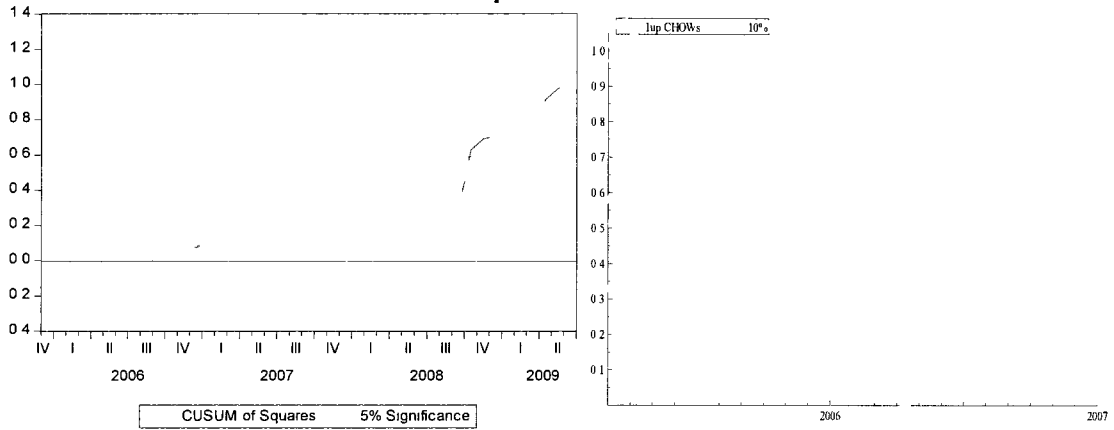
Figure 4.16
Structural Change Results Based on CUSUMSQ and 1-Step Chow Test
Sample: 1959:01-2009:06
LNSP500
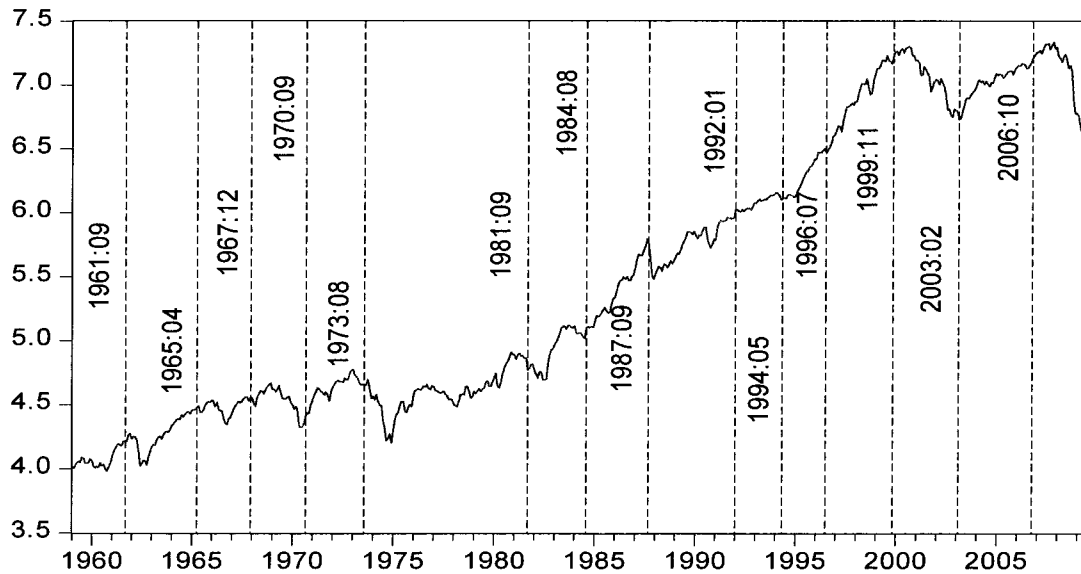
Figure 4.17
Structural Change Results and *Bloomberg* Instability
Sample Period: 1993:01-2009:12
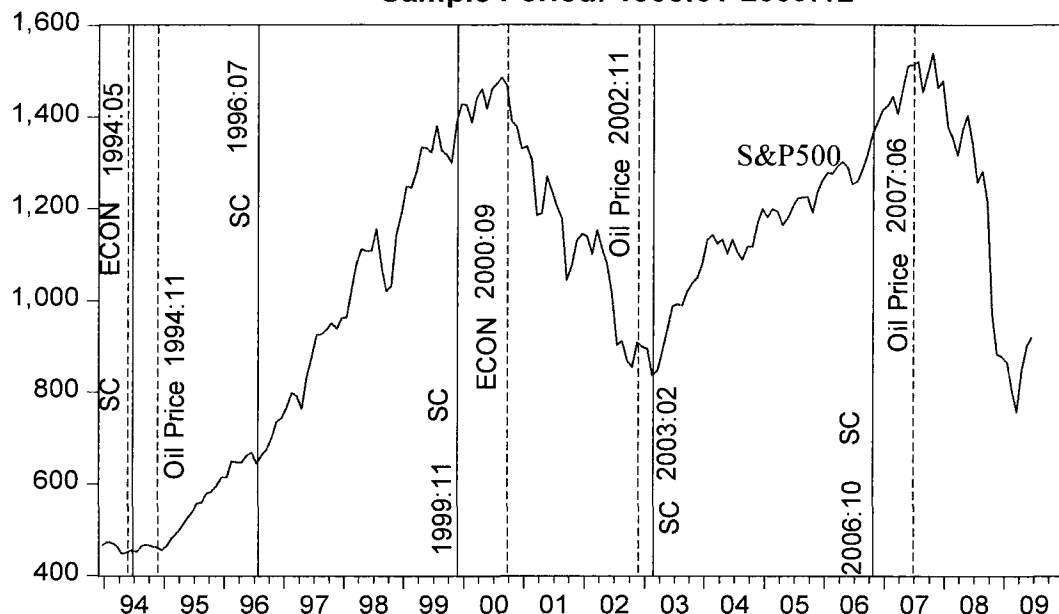
Notes: The figure plots the formal econometric structural change results, denoted by "SC" and a solid line, against the instability analysis based on *Bloomberg*, denoted by dotted lines. "ECON" and "Oil Prices" correspond to the shifts in directional relationships pertaining to those fundamental factors. The dates of the breakpoints are plotted along-side the description of each breakpoint.

Figure 6.1
Interest Rates Based on *Bloomberg News's* and 3-Month T-Bill
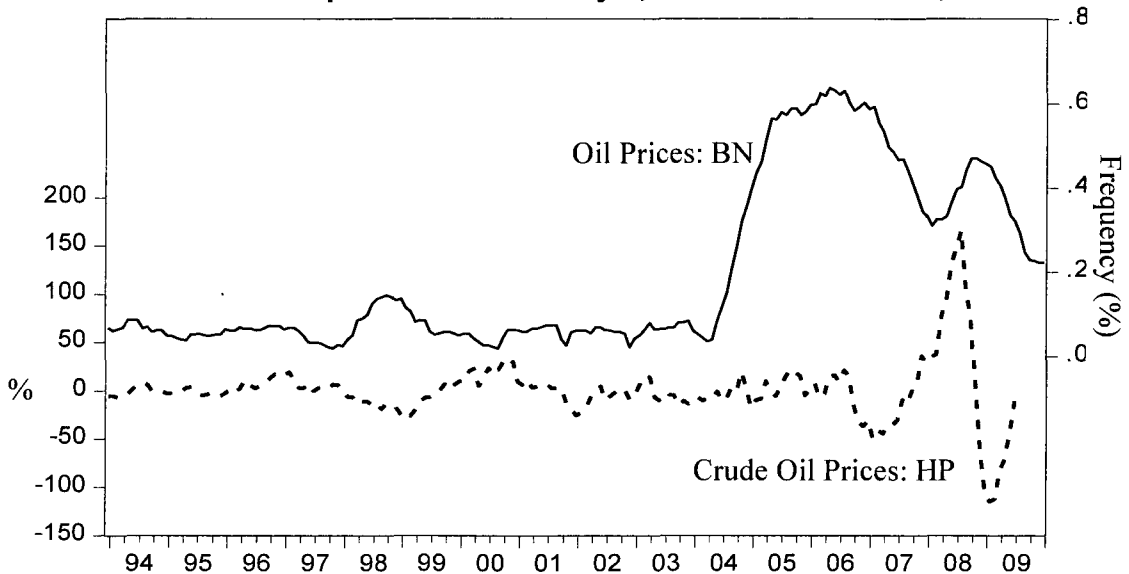## Sample: January 4, 1993 – December 31, 2009
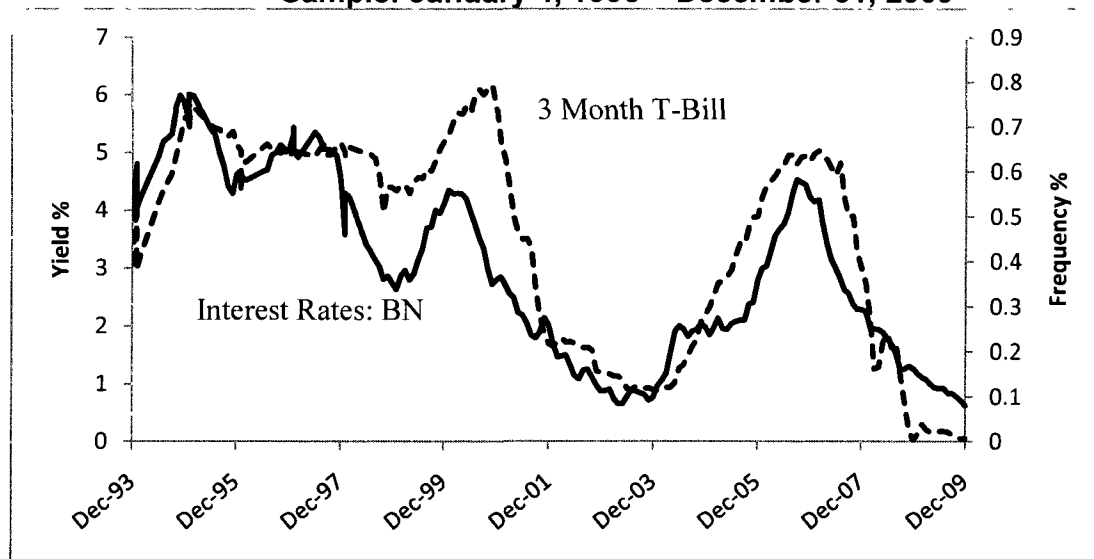
Notes: The solid line denotes the factor frequency of interest rates based on the *Bloomberg* data. The dotted line denotes the actual 3-month Treasury bill yield.

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Figure 6.2
Oil Prices Based on *Bloomberg News'* and Crude Oil Prices
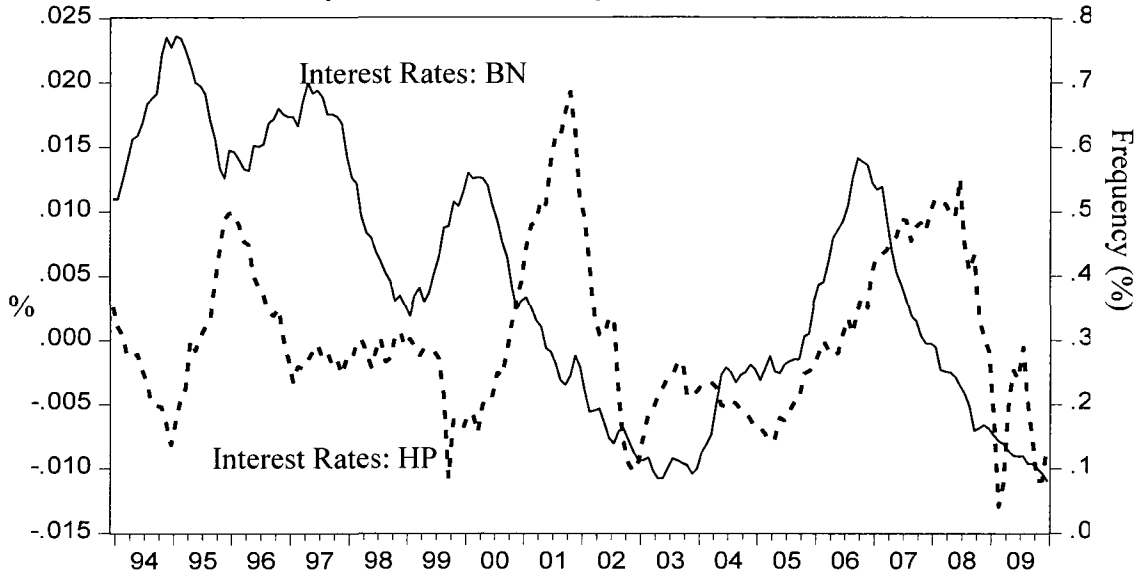### Sample: January 4, 1993 – December 31, 2009
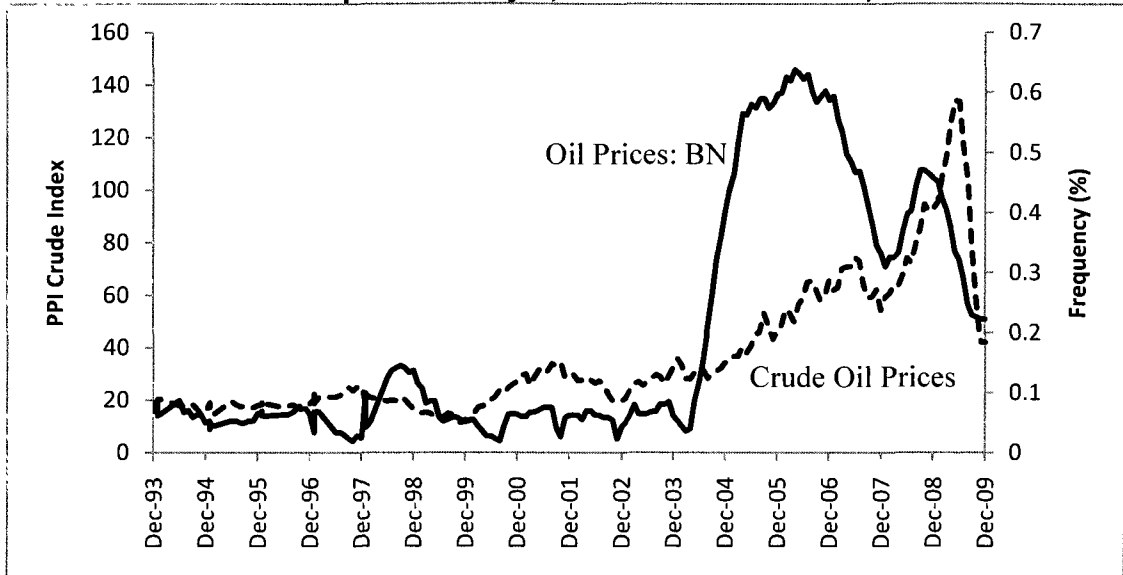
Notes: The solid line denotes the factor frequency for oil prices based on the *Bloomberg* data. The dotted line denotes the actual Producer Price Index for Crude Petroleum.

Figure 6.3
Oil Prices Based on *Bloomberg News'* and Oil Price-Gap
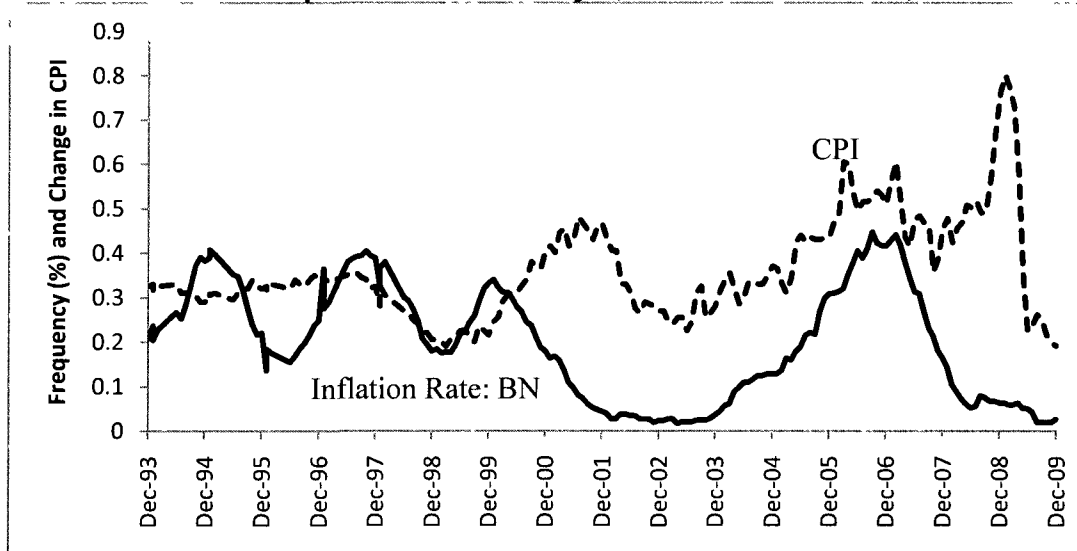### Sample Period: January 4, 1993- December 31, 2009

Notes: The solid line denotes the factor frequency of oil prices based on the *Bloomberg* data. The dotted line denotes the magnitude of the deviation from the trend component in actual crude petroleum prices calculated by the HP Filter.

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Figure 6.4
Interest Rates Based on *Bloomberg News'* Market Wraps
and the Interest Rate-Gap
## Sample Period: January 4, 1993-December 31, 2009

Notes: The solid line denotes the factor frequency of interest rates based on the *Bloomberg* data. The dotted line denotes the magnitude of the deviation from the trend component of actual 3-month T-bills calculated by the HP Filter.

Figure 6.5
Inflation Rates Based on *Bloomberg News'* Market Wraps
and Change in the CPI
Sample Period: January 4, 1993-December 31, 2009

Notes: The solid line denotes the factor frequency of inflation rates from the *Bloomberg* data. The dotted line denotes the monthly change in the CPI (Consumer Price Index). This series is smoothed by a 20-year average.

Figure 6.6
Economy Based on *Bloomberg News'* Market Wraps and
Negative Growth in Industrial Production
Sample Period: January 4, 1993-December 31, 2009
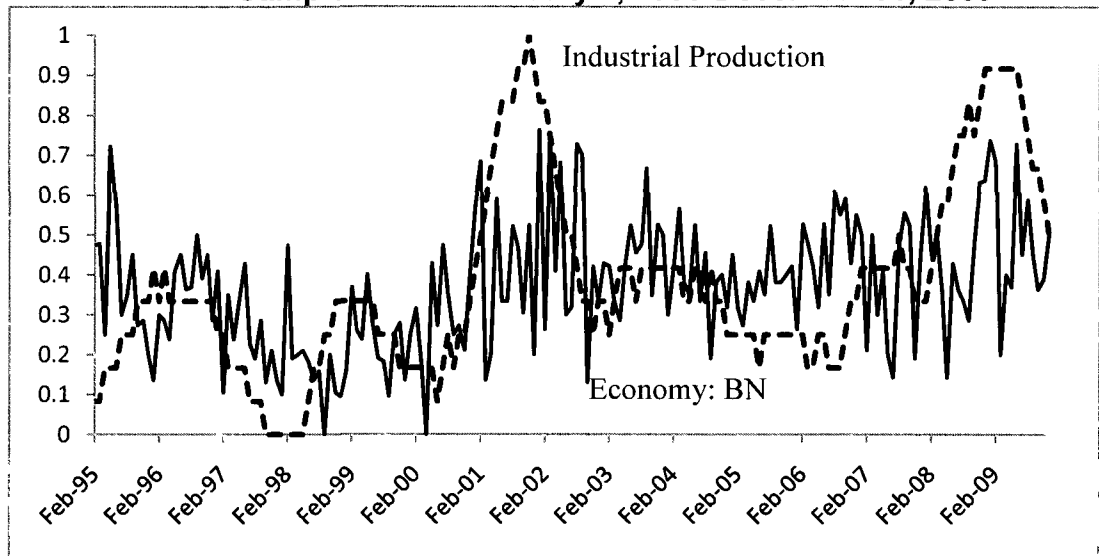
Notes: The solid line denotes the factor frequency for the economy (without smoothing it over a 12-month period) based on the *Bloomberg* data. The dotted line is a monthly measure capturing negative growth rates for Industrial Production. This series is generated as follows. Each month is scored with a one or a zero if Industrial Production experienced negative or positive growth from last month to the current month, respectively. This series is then smoothed over the previous twelve months.