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Fundamental factors and extrapolation in stock-market expectations: The central role of structural change[☆]

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ABSTRACT

Rational expectations and behavioral-finance models are widely interpreted as representing two distinct conceptions of decision-making: rational and irrational, respectively. Using survey data, this paper presents econometric evidence that both fundamental factors and extrapolation drive participants' expectations of stock returns, but that they do so in ways that vary over time. Although both the REH and behavioral-finance approaches offer relevant insights for understanding participants' expectations, neither of these distinct model classes is consistent with time-series data. The paper's findings also suggest that structural change gives rise to ambiguity about the correct quantitative model driving outcomes. This ambiguity, faced by economists and market participants alike, is the key to according both fundamental and behavioral factors a role in *rational* forecasting.

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1. Introduction

Rational expectations and behavioral-finance models are widely interpreted as representing two distinct conceptions of decision-making: rational and irrational, respectively. The rational expectations hypothesis (REH) represents how rational participants forecast stock returns in terms of fundamental factors, such as company earnings and interest rates. By design, REH models rule out the relevance of extrapolation of past returns, or optimism (pessimism) concerning the course of prices, in driving participants' expectations of future returns. In contrast, behavioral-finance models assume that such considerations are a primary driver of stock-market expectations. For example, evidence that participants' expectations are at least in part extrapolative is considered to be a symptom of market participants' "less than full rationality".¹

Using survey data, this paper presents econometric evidence that both fundamental factors and extrapolation drive participants' expectations of stock returns, but that they do so in ways that vary over time. As in any econometric investigation,

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¹ For extensive surveys of the behavioral-finance approach, see [Shleifer \(2000\)](#), [Barberis and Thaler \(2003\)](#), and references therein.

our findings are conditioned on the empirical specification of the model for investors' expectations. Although our specification includes a set of commonly used fundamentals and proxies for extrapolation, it is possible that inclusion of additional variables might alter the findings on structural breaks. Importantly, these breaks may be capturing the effect of prevailing narratives about the future course of stock prices (Shiller, 2017).² Nonetheless, our findings suggest that, although both the REH and behavioral-finance approaches offer relevant insights for understanding stock-market expectations, neither of these distinct classes of models is consistent with empirical evidence.

Our finding that fundamentals are a major driver of participants' expectations is the key insight formalized by REH models. However, a typical REH model constrains its structure – the set of explanatory variables and their parameters – to be time-invariant. This makes the model inconsistent with structural breaks in how fundamentals drive stock-price expectations.

REH models sometimes allow for structural change. But when they do, they represent it with a probabilistic rule, such as Markov switching. In a number of papers, David Hendry has not only demonstrated the empirical relevance of structural change in a variety of contexts, but has also shown that such change is often triggered by historical events that are, at least in part, unique. This implies that the timing and the magnitude of these structural shifts could not have been foreseen with a probabilistic rule, thereby invalidating REH models.³

Moreover, the apparent significance of extrapolation that we find is inconsistent with REH models, *regardless* of whether they allow for structural change. At the same time, while extrapolation plays an important role in behavioral-finance models' accounts of asset-price swings, these models typically assume that its effect is time-invariant. In contrast, we find that the effect of extrapolation, like that of fundamentals, varies over time.

Although consistent with neither REH nor typical behavioral-finance models, our finding of structural change suggests a way to build on the insights of both approaches. As we discuss in the concluding remarks, recognizing that participants rely on fundamental and behavioral factors in ways that vary over time is the key to accounting for the role of both sets of factors in *rational* forecasting.

By contrast, the previous studies of participants' expectations using survey data, like much theoretical and econometric modeling, constrain the structure of the empirical specification to remain unchanging over time. These studies have concluded that participants' expectations are largely extrapolative, while fundamental factors play a negligible role. Such studies are generally interpreted as supportive of the behavioral-finance approach.⁴ But by relying on time-invariant specifications, these studies may have obscured the variation in the impact of fundamentals that might arise from participants' revisions of their forecasting strategies. Likewise, the impact on expectations of behavioral considerations such as extrapolation may change over time.

Indeed, long-standing, largely overlooked arguments suggest that we should expect models that include such behavioral factors to be structurally unstable. Behavioral-finance theorists have formalized their effect with representations that are inconsistent with the predictions of an economist's model. As Lucas (2001, p. 13) argued, such non-REH representations presume that participants are grossly irrational, in the sense that they ignore systematic forecast errors in perpetuity. We would expect that, faced with such errors, participants would revise their forecasting strategies. Moreover, beyond responding to forecast errors, participants may also alter the way they interpret fundamentals in response to changes in monetary regimes (Lucas, 1976), evolving technologies, political institutions, and a multitude of other factors (Frydman and Goldberg, 2011). Akerlof and Snower (2016) argue that participants' interpretation of the process driving outcomes is to a significant extent influenced by their shared narrative accounts of the determinants of this process and how it might change over time. They argue that these narratives “play a role in understanding the environment, ... predicting events, ... [and] motivating actions (p. 59).” Participants' reliance on narratives may lead them to alter the weights that they attach to various factors in forming their expectations.

Thus, if both fundamental and behavioral variables are relevant for understanding participants' expectations, we would expect structural breaks in the parameters of both sets of factors. And this is precisely what we find: the parameters of fundamentals, extrapolation, and all other factors in our specification of participants' expectations undergo intermittent breaks during the sample period.

The myriad potential sources of change in how fundamental and behavioral considerations might affect investors' expectations would seem to preclude a theoretical account that could predict when and how investors might revise their forecasting strategies. In the absence of such a theory, we use the multiplicative indicator saturation (MIS) procedure, which does not require that we specify in advance the mechanism behind and timing of structural breaks.

The MIS procedure, proposed by Ericsson (2012), extends the automated model selection (Autometrics) algorithm of Hendry and Krolzig (2005) and Doornik (2009). The superior properties of this approach relative to other approaches to model selection have been documented in that literature.⁵

² Frydman et al. (2018) examine structural change in stock-market expectations using the proxies extracted from narrative market reports. They provide evidence that the time-varying effects of fundamentals are associated with variation in market sentiment: participants' optimism (pessimism) about future stock returns.

³ See Hendry (2017) and references therein.

⁴ For recent studies using stock-market survey data, and references to earlier literature, see Williams (2013) and Greenwood and Shleifer (2014).

⁵ For an in-depth treatment of the automatic model-selection procedures, see Hendry and Doornik (2014).

In contrast to other procedures, such as [Bai and Perron \(1998\)](#), MIS does not constrain the breaks in the parameters of each variable to occur at the same time. This is important because we have no reason to suppose that structural breaks in all variables occur simultaneously. In general, for example, we might expect parameters of fundamental and behavioral factors to break at different times.

We apply the MIS procedure at stringent significance levels of 0.01%, which ensures that only one in 10,000 breaks, on average, would be falsely included. This conservative approach is biased toward missing smaller parameter changes, in order to avoid erroneously included breaks.

Beyond estimating structural breaks, the MIS procedure enables us to correct for the selection bias arising from the repeated re-estimation of the empirical specification, which is required to identify relevant variables based on their statistical significance. As we discuss in [Section 3](#), MIS's selection-bias correction makes improbable that many, let alone all, of the highly significant breaks that we retain were incorrectly estimated.

We rely on the MIS procedure to select the empirical specification for participants' expectations of one-year-ahead stock returns. The set of fundamental variables retained by MIS includes dividend growth, earnings growth, the inflation rate, and the change in the one-year Treasury bill rate. MIS also finds that two proxies for extrapolation play a significant role in driving expectations. Finally, MIS uncovers a previously unreported inertia effect: expectations of returns depend strongly on their lagged values.

These results show that both REH and behavioral insights matter for understanding participants' expectations. However, as we discussed earlier, our findings are inconsistent with the time-invariant specifications upon which both of these approaches typically rely to formalize their insights. Despite our very stringent criterion for structural change to be retained by MIS, the procedure estimates multiple breaks in the parameters of both fundamental and behavioral factors.

Remarkably, although the parameters of dividend and interest rate changes undergo structural change in our model, their signs do not; remaining positive and negative, respectively, throughout the sample period. As we discuss in the concluding remarks, these findings point to a novel interpretation of the path-breaking arguments of [Shiller \(1981\)](#) concerning the empirical difficulties of the REH present-value model.

The structure of the paper is as follows: [Section 2](#) describes the survey data; [Section 3](#) sketches the MIS procedure, and discusses how it estimates structural breaks and corrects for the selection bias; [Section 4](#) summarizes the MIS results; and [Section 5](#) discusses the implications of our findings, and of the central role of structural change, for developing an approach that builds on REH and behavioral-finance insights to accord both fundamental and behavioral factors a role in *rational* forecasting.

2. Survey data

The availability of survey data has made it possible to investigate directly whether REH and/or behavioral-finance insights matter for understanding investor expectations. However, given its sensitivity to question framing and interpretation, evidence from survey data has been considered unreliable. It is argued that the surveys are either too noisy or unrepresentative to be useful, or that respondents are misinterpreting the question ([Cochrane, 2011](#)).

[Greenwood and Shleifer \(2014\)](#) convincingly argue against this dismissal of stock-market survey data. GS use seven proxies summarizing different surveys of investors' expectations. An important contribution of their paper is to show that these proxies are highly correlated with market participants' decisions to invest their capital in mutual funds. Furthermore, GS show that the proxies co-move strongly and positively, even though the surveys that underpin them rely on very different methodologies. This evidence buttresses their argument that the evidence surveys produce is not just "meaningless noise" (p. 715).

In this paper, we use the proxy for investors' expectations that summarizes the survey by the *Investors Intelligence Newsletter* (IIN), which is the longest survey among those studied by GS. The IIN survey records the percentage of its participants' bullish, neutral, and bearish forecasts on a weekly basis. Given that most of the other variables are measured at monthly intervals, we use a monthly average. Moreover, we denote by $Exp_{t+12|t}$ investors' time- t expectation of percentage stock returns over the succeeding 12-month period, $t+12$. Following GS, we proxy $Exp_{t+12|t}$ with the difference between the proportion of investors who are bullish and bearish at t concerning stock prices at $t+12$:

$$Exp_{t+12|t} = [\% \text{ bullish}_t - \% \text{ bearish}_t] \quad (1)$$

Measures computed according to (1) do not yield numerical observations of price changes expected by survey participants. However, GS show that such proxies are highly correlated with the shorter sample available from Gallup surveys, which provide numerical forecasts of stock returns from September 1998 through May 2003.

3. Autometrics and the multiplicative indicator saturation (MIS) procedure

We use the Autometrics tree-search algorithm of [Doornik \(2009\)](#) to select the econometric model for participants' expectations and correct for the model-selection bias arising from repeated searches from the same set of potential explanatory variables. A key feature of the Autometrics algorithm is that it buttresses reliable inference: it selects only those specifications that pass a battery of standard tests for specification error.

3.1. Model selection and structural breaks

Autometrics provides a disciplined way to select an econometric specification involving a subset of variables chosen from a large potential set of regressors. This is crucial in examining the relevance of the REH and behavioral-finance insights. These approaches' predictions concern broad sets of factors – fundamental and behavioral, respectively, that might be relevant for understanding participants' expectations. Thus, in order to ascertain whether any of these factors drive expectations, an investigator must examine a variety of potential specifications involving different subsets of some large set of candidate variables. Autometrics does so in a disciplined way, by requiring that the selected model pass a battery of specification error tests.

We estimate a model of participants' expectations by relating the IIN survey proxy to a set of fundamental factors and the variables that represent extrapolation. The Autometrics procedure relies on the general-to-specific methodology, whereby all potential variables are included from the outset.

In order to facilitate comparison with earlier literature, we include the same set of potential variables as that used by GS.⁶ Their set of extrapolative variables consists of the percentage change in the S&P 500 over the last year (the measure of past returns) and the log of the price-dividend ratio. Fundamental variables used by GS include: unemployment, the risk-free interest rate, the growth rate of earnings, industrial production, and consumption.

Using the Augmented Dickey–Fuller test (Said and Dickey, 1984), we show in Table A.1 that we can not reject a unit root for the interest rate, unemployment, or the log price-dividend ratio; three of the five variables used in GS's presented results for models including fundamentals. In order to avoid spurious regressions and the unreliable inference that including such variables might cause, we use first differences for these non-stationary variables in formulating our model of participants' expectations. Consequently, our application of Autometrics includes the following variables:

$$X_i = [Exp_{t+11|t-1}, R_{t|t-12}, \Delta(P_t/D_t), \Delta u_t, \Delta i_t, \Delta \ln(E_t), \Delta \ln(C_t), \Delta \ln(D_t), \Delta \ln(Y_t), \Delta \ln(CPI_t)]$$

which denote, respectively, the lagged expectation, the past 12 months' return, the change in the log price-dividend ratio, the change in unemployment, the change in the one-year Treasury bill rate, the change in log earnings, the change in log personal consumption expenditure, the change in log dividends, the change in industrial production, and CPI inflation.

3.2. Estimating structural breaks

We allow for time variation in the coefficients of these variables by relying on the multiplicative indicator saturation (MIS) application of Autometrics, proposed by Ericsson (2012) and examined by Kitov and Tabor (2015).⁷ MIS estimates structural breaks by interacting each variable with a step indicator for each observation $\mu_j 1_{\{t \leq j\}}$. The step indicator [1,1,1... 1,0,0,...] is specified as equal to 1 until time period j , and equal to 0 thereafter. This is done from the first observation to the second-to-last ($T - 1$) observation for each of the n variables, to allow for a change in the coefficient of any variable at any point in time relative to the full-sample estimate. The Autometrics tree-search algorithm is used to select across these $n * (T - 1)$ step indicators (possible coefficient breaks), where n is the number of variables, and T is the sample size of the time-series observations of these variables. We specify the initial, unrestricted model as follows:

$$Exp_{t+12|t} = \sum_{i=1}^{10} \beta^i X_i^t + \sum_{i=1}^n \sum_{j=1}^{T-1} \beta^{ij} \mu_j 1_{\{t \leq j\}} X_i + \sum_{i=1}^T \delta_i 1 + \sum_{j=2}^T \mu_j 1_{\{t \leq j\}} + \varepsilon_t \quad (2)$$

This specification allows for the possibility that expected returns are a function of the lagged expectations, fundamentals, and extrapolative proxies contained in $\sum_{i=1}^{10} \beta^i X_i^t$. We also allow for the possibility of breaks in the coefficients of these regressors through the $n * (T - 1)$ multiplicative indicators $\sum_{i=1}^n \sum_{j=1}^{T-1} \beta^{ij} \mu_j 1_{\{t \leq j\}} X_i$. Lastly, we allow for dummy variables for outliers and potential mean shifts in the constant via $\sum_{i=1}^T \delta_i 1$ and $\sum_{j=2}^T \mu_j 1_{\{t \leq j\}}$.⁸

Given that one of the main objectives of this study is to demonstrate the empirical relevance of structural change, we select a very stringent significance level of 0.01% in selecting the variables through Autometrics, implying that the search algorithm would falsely retain only one in 10,000 breaks. Moreover, by design, all four of the model-specification tests (autocorrelation, normality, heteroskedasticity, and ARCH) will not be significant at the 1% level in the final model estimated by the MIS procedure.⁹

3.3. Correcting for selection bias

Beyond estimating structural breaks, the MIS procedure enables us to address another important difficulty inherent in empirical modeling of expectations: selection bias arising from repeatedly searching among alternative specifications involv-

⁶ GS selected the model by manually re-estimating the specification of participants' expectations and selecting variables on the basis of their significance levels.

⁷ MIS differs from the approach commonly used with Autometrics in that the latter allows for breaks only in the empirical model's constant term (Castle et al., 2015; Hendry et al., 2008). For finance applications of Autometrics, see Bekaert and Hoerova (2014), Stillwagon (2016), and Stillwagon (2017).

⁸ Note that the latter is summed beginning only in the second observation, because an impulse dummy and step indicator, as specified, are identical in the first observation.

⁹ Hendry and Krolzig (2005) advocate using the 1% significance level, because it corresponds to rejecting an adequate model on the basis of one of the tests approximately 5% of the time. Using 5% for each test would result in a far larger type I error on the basis of one of the four tests.

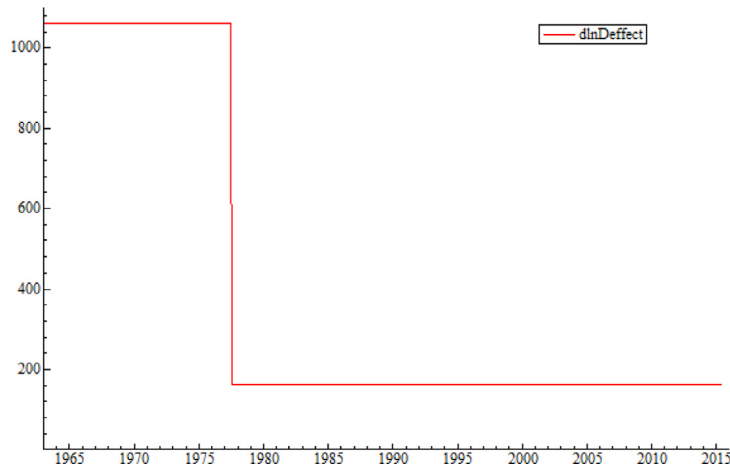


Fig. 1. The effect of dividend growth over time.

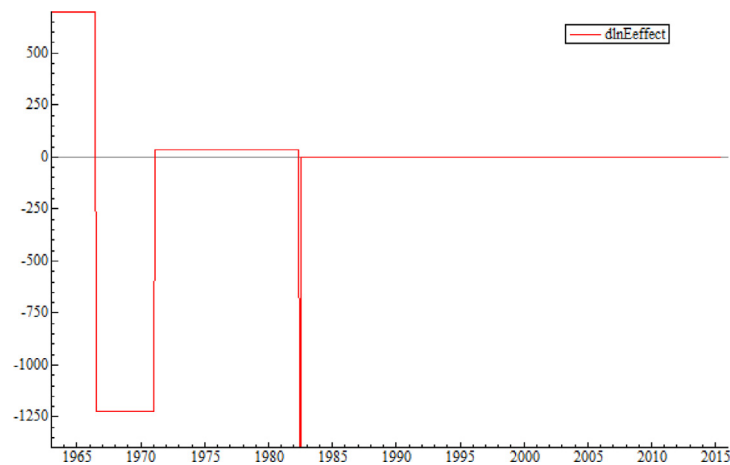


Fig. 2. The effect of earnings growth over time.

ing the same set of variables. Manually selecting the final model, as is commonly done, leaves the potential for confirmation bias (Campos, 2005). Moreover, searching for factors through repeated re-estimation of the empirical specification, and retaining relevant variables on the basis of their statistical significance, typically results in inflated t-ratios, and thus biased inference (Lovell, 1983).¹⁰

MIS applies a correction to address the upward biases of the R-square and absolute t-values resulting from such repeated searches. As shown rigorously in Hendry and Krolzig (2005), the estimates from the general-to-specific algorithm are consistent after the bias-correction. The correction has the effect of pushing the coefficients toward zero, with the magnitude of adjustment dependent on the estimated t-value. This helps to mitigate the problem of falsely included variables. It is thus improbable that many, let alone all, of the highly significant structural breaks that MIS retains were incorrectly estimated.

4. Results

Table A.2 in the appendix displays the results from MIS. This estimate is the sum of the full-sample estimate and any relevant multiplicative indicators at that point in time. A model-selection-bias correction is then applied to the estimates. For ease of interpretation, we present the results visually in Figs. 1–6 for any variable with a significant structural break. The figures present the timeplot of estimated coefficients.

¹⁰ For example, GS reach their conclusion that investors' expectations are extrapolative, with fundamental factors playing a negligible role, by repeatedly re-estimating specifications involving subsets of the same set of explanatory variables.

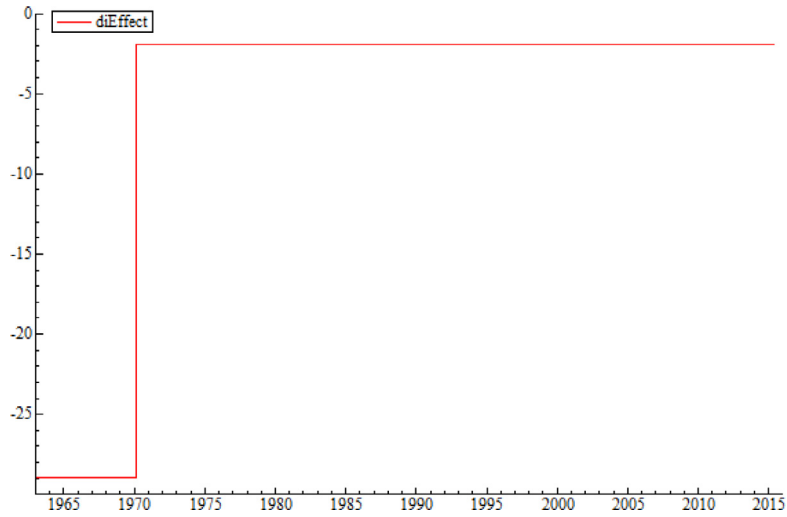


Fig. 3. The effect of changes in the interest rate over time.

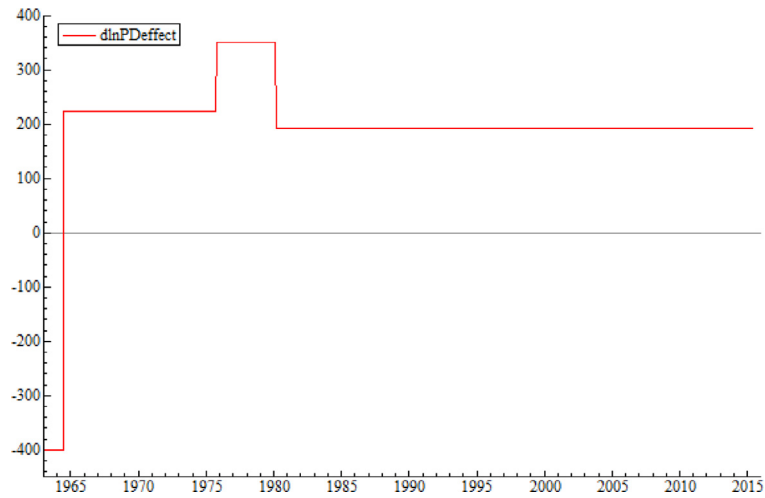


Fig. 4. The effect of the change in the log price-dividend ratio over time.

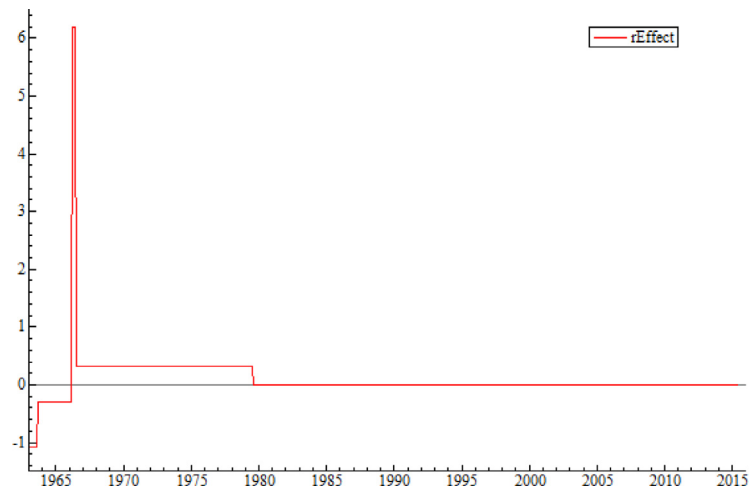


Fig. 5. The effect of the previous 12 months' return over time.

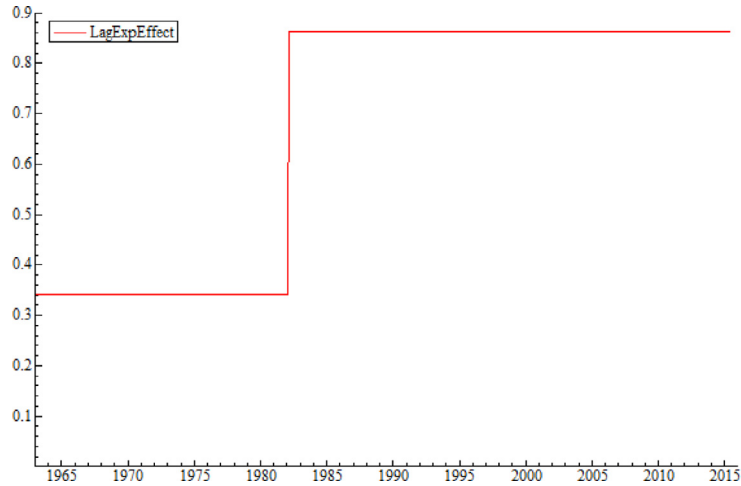


Fig. 6. The effect of expectations inertia over time.

4.1. Fundamentals

We find that participants' stock-returns expectations co-move positively with the growth rate of dividends, $\Delta \ln(D_t)$. The effect of the dividend-growth rate undergoes structural change in our model, falling significantly in 1977:07.¹¹ However, it remains positive and significant over the full sample.

We also find that company earnings influence expectations of stock returns in a way that is not captured by dividends. The effect is positive in the early part of the sample, as well as during the period from 1971:02 to 1982:05. It becomes insignificant after 1982:07.

However, there is a period of roughly five years from 1966:07 to 1971:01 when the coefficient on earnings turns negative, though the effect of dividends remains positive. We leave for future research an investigation of why, after controlling for the effect of dividend growth and the other variables in our model, earnings have a negative effect on expectations of stock returns during the mid-1960s.

We also find that interest-rate changes impact expectations negatively throughout the sample. As with dividend and earnings growth, interest rates drive participants' expectations in ways that vary over time in our model. The magnitude of their effect falls dramatically beginning in 1970:03, though it remains negative and statistically significant throughout the sample.

Inflation, $\Delta \ln(CPI_t)$, has a fixed, negative coefficient throughout the sample. The negative sign is consistent with a Taylor rule-like model, whereby higher inflation gives rise to expectations of future interest-rate tightening by the Federal Reserve.¹²

4.2. Extrapolation

The effect of extrapolation seems to derive primarily from the monthly change in the log price-dividend ratio, $\Delta(P_t/D_t)$, as opposed to the return over the previous 12-months $R_{t|t-12}$. In the earliest portion of the sample, from 1963:02 to 1964:06, the effect of the short-term extrapolation is actually negative. This effect implies that, in the beginning of our sample, investors expected that stock prices would mean revert, but began extrapolating the past month's change, *ceteris paribus*, in 1964:07. From 1975:10 to 1980:02, the effect of extrapolation increases; thereafter, it declines, though it remains highly significant.

The effect of the previous 12 months' return, like our other proxy for extrapolation, is negative in the earliest part of the sample. This expected mean reversion diminishes after 1963:08, but remains negative until 1966:04. Then it becomes slightly positive through 1979:07. Thereafter, the effect of longer-term extrapolation $R_{t|t-12}$ is no longer statistically significant even at conventional levels. As Fama (1998) predicted, these behavioral influences proved unstable, at the 0.1% level based on MIS, even in a qualitative sense. However, some degree of extrapolation does prevail over the majority of the sample.

¹¹ We noted in the introduction that any findings of structural change are conditional on the chosen information set. Frydman et al. (2018) trace the structural change in stock-price expectations to changes in market sentiment about the future course of prices.

¹² Taylor rule models have become prevalent in the exchange-rate literature. See, for example, Molodtsova et al. (2008) and Mark (2009).

4.3. Expectations inertia

Beyond revealing the qualitative effects of fundamental and behavioral factors, MIS uncovers a hitherto unrecognized feature of participants' expectations: they are characterized by time-varying inertia. We find that the lagged expectations have a large and highly significant impact on current expectations, even after controlling for fundamentals and past returns.

The effect of expectations inertia is consistently positive, but its magnitude more than doubles in March 1982 in our empirical specification. Up to 1982:02, *ceteris paribus*, investors expected the return to be 34% of what they expected in the previous period; thereafter, they expected 86% of the return they expected in the previous period. In this sense, the degree of bullishness and bearishness decays only slowly, and this became more pronounced in 1982.

The substantial increase in the degree of expectations inertia in 1982 is proximate to the beginning of the long bull market. Shiller (2000) points to numerous factors that may have contributed to the upswing of the 1980s and 1990s, including the shift from defined-benefit to defined-contribution pension plans, the increase in financial news on TV, lower trading costs from online platforms, and the reemergence of mutual funds. These factors may have similarly contributed to an increase in expectations inertia, as broader stock-market participation by more novice investors ensued. Future research will need to account for inertia's significance, and its abrupt increase in magnitude in the early 1980s.

5. Concluding remarks

In a path-breaking paper, Shiller (1981) presented evidence that the REH present-value model is inconsistent with the quantitative co-movements between dividends and stock prices in time-series data. Although we found, in the context of our empirical specification, that the quantitative effects of dividends and interest rates on participants' expectations undergo structural breaks, their qualitative effects, as represented by their signs, do not change throughout the sample period. Remarkably, the coefficients of the dividend-growth rate and change in the Treasury bill rate remain positive and negative, respectively.

Shiller, and subsequent researchers who corroborated his findings, interpreted REH models' difficulties as evidence that market participants' expectations, and thus stock-price swings, are driven by psychological and technical considerations. Our MIS specification is qualitatively consistent with the behavioral-finance insight that extrapolation is an important driver of market participants' stock-price expectations. However, in contrast to the time-invariant formalizations in behavioral-finance models and previous empirical work, these effects vary dramatically over time.

Like their REH counterparts, behavioral-finance models assumed away the possibility that the structural change we document may be, at least in part, unforeseeable. The defining feature of such change is that it cannot "by any method be [represented *ex ante*] with an objective, quantitatively determined probability" (Knight, 1921, p. 321). Having assumed away unforeseeable change, behavioral-finance models had no alternative to presuming that market participants are irrational, in the sense that they ignore systematic forecast errors.¹³

5.1. A Way Forward?

Aiming to build models that do not presume such gross irrationality, Frydman et al. (2017b) developed an approach that opens macroeconomics and finance theory to unforeseeable change in the process driving outcomes. Our findings, especially those concerning highly irregular structural breaks in the behavioral factors driving expectations, appear consistent with the idea that such breaks could not be foreseen with a probabilistic rule, such as, for example, Markov switching.

As Knight pointed out, unforeseeable change gives rise to ambiguity about which is the correct quantitative model driving outcomes. Frydman et al. (2017b) propose a mathematical framework, which they call the Qualitative Expectations Hypothesis (QEH), that formalizes limits to what economists and market participants know about future outcomes. They use QEH to represent expectations in the context of the present-value model for stock prices.

Frydman et al. (2017b) show that by recognizing ambiguity on the part of economists and market participants, a QEH model can account for the role of both the fundamental factors on which REH models focus and the psychological factors underpinning behavioral-finance models. And it can do so without presuming irrationality on the part of market participants.

Because a QEH model is open to unforeseeable change, it implies that there are myriad possible model-consistent quantitative forecasts. Thus, in making decisions – for example, about how many stocks to buy or sell – market participants face inherent ambiguity. They select particular quantitative forecasts by relying on a combination of considerations, including formal (econometric) models, market sentiment, and other non-fundamental factors. A QEH model can formalize the qualitative effect of such factors on participants' model-consistent forecasts, by imposing additional restrictions on how market participants revise their forecasting strategies.

Although a QEH model can account for the role of both fundamental and behavioral factors that we find empirically relevant in this paper, more research is required to ascertain whether the model can generate the more specific results of our econometric analysis. Given Shiller's conclusion, and that of subsequent researchers, that the REH present-value model is inconsistent with the quantitative co-movements in time-series data, a question that is of particular interest is whether the QEH version of the model can account for qualitative co-movements between stock prices and fundamental factors.

¹³ For a rigorous demonstration in the context of the present-value model for stock prices, see Frydman et al. (2017a).

Appendix

Table A.1

Unit root tests the values are the *p*-values from the Dickey Fuller tests of the null of a unit root.

	ADF w/ trend	ADF w/o trend
II $Exp_{t t+12}$	0.0000	0.0000
AA $Exp_{t t+12}$	0.0000	0.0000
$\ln(P_t/D_t)$	0.4759	0.5550
$\Delta \ln(P_t/D_t)$	0.0000	0.0000
u_t	0.1599	0.0440
i_t	0.2678	0.4299
Y_t	0.2500	0.2462
E_t	0.0000	0.6752
D_t	0.0026	0.9212
C_t	1.0000	0.0000

Table A.2

MIS Results at 0.01% with Full Sample Estimates Fixed. The step indicator following a variable (SYMM) marks the year YY and month MM up until which the indicator (or differential effect from the variable's estimate) is relevant. The two outlier dummy variables (IYYMM) and the multiplicative indicators in the right column are selected at a 0.01% significance level. The reported coefficients and t-values are after the selection-bias adjustment.

	Coefficient [t-value]		Coefficient [t-value]
Const.	1.882 [3.13]	$Exp_{t-1} * S8202$	-0.521 [-2.71]
Exp_{t-1}	0.862 [36.70]	$Exp_{t-1} * S7103$	0.921 [3.13]
Δu_t	-2.044 [-1.06]	$Exp_{t-1} * S7102$	-0.994 [-3.38]
Δi_t	-1.928 [-2.63]	$Exp_{t-1} * S6308$	-11.763 [6.31]
$\Delta \ln E_t$	-9.822 [-1.65]	$Exp_{t-1} * S6307$	11.711 [6.16]
$\Delta \ln C_t$	6.047 [0.09]	$\Delta i_t * S7002$	-26.999 [-2.85]
$\Delta \ln D_t$	162.295 [2.75]	$\Delta \ln E_t * S8207$	-1391.4 [-2.98]
$\Delta \ln Y_t$	16.405 [0.34]	$\Delta \ln E_t * S8205$	1428.6 [3.09]
$\Delta \ln CPI_t$	-457.161 [-5.15]	$\Delta \ln E_t * S7101$	-1262.4 [-6.68]
$R_{t t-12}$	-0.042 [-1.60]	$\Delta \ln E_t * S6606$	1924.5 [5.74]
$\Delta \ln(P_t/D_t)$	191.065 [18.35]	$\Delta \ln D_t * S7707$	899.40 [5.59]
I6305	38.575 [4.93]	$R_{t t-12} * S7907$	0.318 [3.24]
I7104	-5.765 [4.74]	$R_{t t-12} * S6606$	5.870 [4.00]
		$R_{t t-12} * S6603$	-6.488 [-4.47]
		$R_{t t-12} * S6308$	-0.781 [-2.89]
		$\Delta \ln(P_t/D_t) * S8002$	158.26 [4.23]
		$\Delta \ln(P_t/D_t) * S7509$	-125.99 [2.65]
		$\Delta \ln(P_t/D_t) * S6406$	-624.45 [4.65]

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