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RESEARCH ARTICLE

Are survey stock price forecasts anchored by fundamental forecasts? A long-run perspective

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Abstract
This paper firstly shows that a wide range of asset pricing models, including full information and Bayesian rational expectations models, typically imply that agents use the long-run cointegration relationship between stock prices and fundamentals to forecast future stock prices. However, using several widely used survey forecast datasets, we provide robust new evidence that survey forecasts of aggregate stock price indices are not cointegrated with forecasts of fundamentals (aggregate consumption, dividend, and output), both at the consensus and individual level. We argue that it is crucial to relax investors' common knowledge of the equilibrium pricing function to reconcile this finding.

Keywords Survey expectation · Asset pricing · Cointegration

JEL Classification D84 · G12 · G17

1 Introduction

Expectations play a crucial role in financial markets and asset pricing. The demand for assets today depends on investors' expectations for future fundamentals and prices. As a result, the market price of assets reflects investors' expectations regarding both prices and fundamentals. However, there is a large debate on how to model investors' expectations in stock markets, as discussed in Adam and Nagel (2023). Recent research

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employs survey expectations data to test and discipline the modeling of expectation formation in asset pricing.[1]

The role of asset price expectations, in addition to fundamental expectations, in explaining asset price fluctuations depends on how investors form their expectations. As Adam and Nagel (2023) have stated, a crucial question is whether it is common knowledge among agents (i.e., they know, and they know that other agents know, and they know that other agents know that other agents know,...) that each period asset prices are determined by the discounted value of expected future fundamentals. In full-information rational expectations (FIRE) models, agents typically have this common knowledge, as seen in works such as Lucas (1978).[2] Moreover, a substantial body of literature relaxes the full information assumption but continues to assume that agents possess this knowledge.[3] As a result, agents know the equilibrium pricing function that maps (forecasts of) fundamentals to asset prices and incorporate it into forecasting future stock prices.

Building on the above observation, we firstly derive new testable implications on the formation of agents' stock price expectation in several classes of asset pricing models. We formally show that if agents are endowed with the knowledge of the equilibrium pricing function, there are a large number of cointegration relationships between stock price forecasts and fundamental forecasts. Put differently, the long-run component of stock price forecasts is anchored by the long-run component of fundamental forecasts. Perhaps surprisingly, we show that these relationships between the two forecasts exist even if agents have incomplete information (as in models with consumption sentiment and learning) or heterogeneous beliefs about fundamentals (as in models with "agree to disagree").

Furthermore, using several widely used survey forecast datasets, this paper offers some new evidence on the relationship between forecasts of aggregate stock price indices and fundamental forecasts. Astonishingly, contrary to the model predictions described above, we find robust evidence that survey forecasts of aggregate stock price indices are not anchored by forecasts of macroeconomic fundamentals (consumption, dividend, and output) in the US stock markets from a long-run perspective, both at the consensus and individual level. Our empirical findings remain robust to considerations of several potential econometric issues such as structural breaks, small sample issues and multiple testing problems. Meanwhile, realized stock prices are shown to be cointegrated with fundamentals during the same sample periods. Thus, survey data rejects this aspect of the formation of stock price expectations in a wide range of models with FIRE or Bayesian rational expectations (RE) (including RE models with incomplete information or heterogeneous beliefs).

1 For instance, rational expectations hypothesis is rejected in Greenwood and Shleifer (2014) and Adam et al. (2017). Risk-neutral forecasts of future returns and ambiguity aversion are rejected in Adam et al. (2021). De La O and Myers (2021) and Giglio et al. (2021) highlight the important role for cash flow growth expectations in explaining stock price movements.

2 Other examples of FIRE asset pricing models include Campbell and Cochrane (1999), Jermann (1998), Boldrin et al. (2001), and Bansal and Yaron (2004).

3 Examples of this type of models include consumption learning models (Collin-Dufresne et al. 2016), consumption sentiment (Jin and Sui 2022), and "agree to disagree" heterogeneous beliefs models (Ehling et al. 2018).

Finally, we explore the implications of the survey findings for the modeling of stock price expectation formation and stock pricing. As discussed earlier, the tight link between the long-run component of stock price forecasts and fundamental forecasts arises as a consequence of investors' common knowledge of the equilibrium pricing function. Therefore, it appears natural and crucial to relax this knowledge to reconcile our new survey evidence.[4] Motivated by the survey findings, we formally develop and quantitatively evaluate a stock pricing model that relaxes the common knowledge assumption. Following Adam et al. (2017), we deviate only slightly from the standard RE approach by assuming that agents act optimally based on a system of subjective beliefs that is internally consistent and closely aligned (though not identical) with RE beliefs. Furthermore, we assume that agents form stock price forecasts with adding a judgement component. This is motivated by a body of evidence, mainly based on the special surveys conducted by several central banks, which uncovers a prominent role for judgement in the expectation formation of professional forecasters. This judgement component breaks the tight link between stock price forecasts and fundamental forecasts in the model and hence helps to reconcile the survey findings. We show that the model simultaneously and quantitatively replicates our new survey evidence and several stylized facts of stock pricing (e.g., return volatilities, excess return predictability and equity premium).

The remainder of the paper is organized as follows. Section 2 discusses related literature. Sections 3 and 4 provide new testable implications for stock price expectation formation in asset pricing models with FIRE and incomplete information (or heterogeneous beliefs), respectively. We provide an overview of the survey evidence in Sect. 5. Sections 6 and 7 present new survey evidence at the consensus and individual level, respectively. Several testing issues are addressed in Sect. 8. Section 9 discusses the implications of the survey findings and offers a model which reconciles the finding. Section 10 concludes.

2 Related literature

The paper is related to work that utilizes survey forecasts data to analyze expectation formation. A large literature provides survey evidence that is difficult to replicate under the assumption of FIRE, such as Greenwood and Shleifer (2014) and Adam et al. (2017) in the context of asset pricing, and Branch (2004), Coibion and Gorodnichenko (2015), and Adam et al. (2021) in the context of macroeconomic expectations. Eva and Winkler (2023) use out-of-sample forecast error predictability to test RE. Beyond RE tests, Adam et al. (2021) empirically reject the idea that survey return expectations are risk-adjusted or formed by ambiguity-averse/robust investors. Using Gallup micro-data, Makridis (2022) demonstrates that an increase in economic sentiment or overreaction, influenced by exposure to friends experiencing housing price growth, leads to a significant rise in non-durable consumption expenditures, thus offering new evidence supporting diagnostic expectations.

[4] Examples of models which relax this knowledge include examples include Carceles-Poveda and Giannitsarou (2008), Lansing (2010), Kuang (2014), Branch and Evans (2010, 2011), Boswijk et al. (2007), Adam et al. (2012), Adam et al. (2017) and Stark (2020).

There is a rapidly expanding body of literature which conducts randomized information provision experiments to study expectation formation. Relatedly, in terms of asset pricing, Beutel and Weber (2023) jointly test models of extrapolative beliefs about past stock returns, past fundamentals, rational expectations models, learning about long-run returns, and learning from experts, by utilizing surveys and experiments to establish causality. They find lack of common information and extrapolation are prevalent features in the data and causally influence return expectations. By contrast, we derive and test new implications of asset pricing models for the long-run relationship between stock price forecasts and fundamental forecasts. Our empirical evidence answers a crucial question in asset pricing that whether it is common knowledge among agents that each period asset prices are determined by the discounted value of expected future fundamentals (Adam and Nagel 2023). Furthermore, we develop an asset pricing model with incorporating a lack of common knowledge and extrapolation by investors, mirroring the main findings of Beutel and Weber (2023), to replicate the survey evidence. Binder et al. (2023) study the effects of verbal and non-verbal communciation of interest rate hikes on US consumers' house price expectations. They find that verbal communications have muted effects on average house price expectations but large heterogeneous effects across household groups and non-verbal communication can significantly move house price expectations. Moreover, they provide evidence on selectly recalls of mechanisms in forming expectations about the effects of interest rate hikes on house prices. Kuang et al. (2024) study the effects of macroprudential policy changes on housing market expectations and find that changes in residential loan-to-value ratio have a larger effect on hot housing markets than cold markets. Additionally, in terms of macroeconomy, Andre et al. (2022) find substantial heterogeneity in forecasting the effects of macroeconomic shocks, within experts or households and between the two groups.

D'Acunto et al. (2023b) provide a review of literature which highlights the role of individuals' exposure to price signals in their daily lives, lifetime experiences, social network, and cognition in the formation of inflation expectations. Malmendier and Nagel (2016) find that experienced inflation rates over individuals' lives significantly influence individual inflation expectations. Furthermore, Malmendier et al. (2021) illustrate that FOMC members who have directly encountered higher inflation throughout their lives tend to express higher inflation expectations in their semi-annual Monetary Policy Reports to Congress. Binder and Makridis (2022) analyze the transmission of gas prices to consumer beliefs and expectations about the economy and find an important role for learning from personal experience (living through the recessionary oil crises in the 1970 s). D'Acunto et al. (2021) find a gender gap in inflation expectations and that it only arises within households in which women are solely responsible for grocery shopping. Jiménez-Martínez (2015) develops a model of belief influence through communication in an large exogenous social network. Ok and Savochkin (2022) theoretically identify conditions under which decision-makers adopt the exogeneously suggested prior as her own subjective beliefs and form beliefs accordingly.

A growing literature highlights the role of cognition friction in forming expectations. D'Acunto et al. (2019, 2023a) discover that cognitive abilities (IQ) are predictive of individuals' inflation expectations, surpassing the direct impacts of income, education levels, wealth, and other indicators of economic sophistication; the errors in forecasting inflation decrease steadily with IQ. Additionally, extrapolative beliefs best capture expectation formation by individuals with high IQs, while the expectation formation of individuals with low IQs does not align with existing theoretical models. Gennaioli and Shleifer (2010) and Bordalo et al. (2016) propose diagnostic expectations as a realistic behavioral model of inference based on evidence in cognitive psychology. Bordalo et al. (2019) propose diagnostic expectation based on the representativeness heuristic to explain the joint dynamics of fundamentals, expectations, and returns of these portfolios. Grant et al. (2022) study a model of learning under unawareness and show that the level of awareness expand as information accumulates. Miao and Xing (2024) provide the posterior-based approach to study dynamic discrete choice problems under rational inattention. Hu (2023) introduces a new behavioral bias called "information stubbornness," where the decision maker ignores additional informative signals after encountering a nearly revealing one and may consistently make incorrect choices despite receiving an unlimited number of informative signals. Our empirical evidence, which indicates a lack of knowledge and understanding regarding asset pricing mapping, aligns with these observations.

Finally, this paper is related to work that utilizes survey expectations to discipline the modeling of asset prices. Based on survey data (Malmendier and Nagel 2011, 2016), Nagel and Zhenyu (2022) build an asset pricing model with learning with fading memory about the dividend process to replicate several stock market facts, such as the counter-cyclical risk premium. develops a model that relaxes the FIRE assumption to reproduce many patterns of forecast error predictability in survey data that are inconsistent with RE. Bordalo et al. (2020) find that the macroeconomic expectations of professional forecasters typically overreact to new information at the individual level (but underreact at the consensus level). To reconcile these findings, they combine a diagnostic expectation model of belief formation with a noisy information model of belief dispersion.

The contribution of our paper to the literature is twofold. On the one hand, we formally provide new testable implications in asset pricing theory—from a long-run perspective—for asset pricing models with the assumption of FIRE, incomplete information, and heterogeneous beliefs. On the other hand, we provide new survey evidence on stock price forecasts via a thorough and rigorous testing of these implications using multiple sources of survey forecast data and develop a model to reconcile the evidence.[5]

3 Cointegration restrictions on forecasts in FIRE models

3.1 A general setting

While the primary interest of the paper is the formation of stock price expectations in asset pricing models, this section provides some new testable implications for expectation formation in a more general setting of FIRE macroeconomic and financial models.

[5] In a related paper, Kuang et al. (2022) provide survey evidence that the majority of professional forecasters do not use long-run cointegration relationships to forecast macroeconomic variables.

Those models typically impose a large number of cointegration relationships between endogenous variables and exogenous variables (or among endogenous variables). For instance, standard RE asset pricing models typically imply that there exists cointegration between stock prices and fundamentals (dividend or consumption), such as in Campbell and Cochrane (1999) and Bansal et al. (2012). As a consequence of agents' knowledge under FIRE, the same cointegration relationship exists between forecasts of these variables.

To formalize this observation, we consider the following general model of a variable $\{X_t\}$ from a FIRE model, such as (log) stock price or aggregate consumption, which is represented by

$$X_t = X_t^P + X_t^C, \tag{1}$$

$$X_t^P = \mu + X_{t-1}^P + \sigma_{\epsilon,t}\epsilon_t, \tag{2}$$

$$(1 - \phi(L))X_t^C = (1 + \psi(L))\,\sigma_{\eta,t}\eta_t, \tag{3}$$

$$(1 - \widetilde{\phi}(L))\left(\sigma_{\epsilon,t}^2 - \overline{\sigma}_{\epsilon}^2\right) = \left(1 + \widetilde{\psi}(L)\right)\widetilde{\epsilon}_t, \tag{4}$$

$$(1 - \widehat{\phi}(L))\left(\sigma_{\eta,t}^2 - \overline{\sigma}_{\eta}^2\right) = \left(1 + \widehat{\psi}(L)\right)\widetilde{\eta}_t. \tag{5}$$

This variable contains a unit root. The superscripts P and C stand for the permanent and cyclical component. ϵ_t, η_t, $\widetilde{\epsilon}_t$, and $\widetilde{\eta}_t$ are $i.i.d$ innovations and independent to each other. The variance of ϵ_t and η_t are normalized to 1. $\sigma_{\epsilon,t}$ and $\sigma_{\eta,t}$ are allowed to be time-varying and their mean is constant and positive, i.e., $\overline{\sigma}_{\epsilon}^2$ and $\overline{\sigma}_{\eta}^2$. $\phi(L) = \phi_1 L + \phi_2 L^2 + \cdots + \phi_p L^p$ and $\psi(L) = \psi_1 L + \psi_2 L^2 + \cdots + \psi_q L^q$ where L is the lag operator. $\widetilde{\phi}(L)$, $\widetilde{\psi}(L)$, $\widehat{\phi}(L)$ and $\widehat{\psi}(L)$ are similarly defined.[6] The roots of $1 - \phi(z) = 0$, $1 - \widetilde{\phi}(z) = 0$, and $1 - \widehat{\phi}(z) = 0$ are within the unit circle, so X_t^C is a stationary process.

Given the assumption of FIRE, agents know the law of motion of X_t (equation (1)-(5)) and make use of this knowledge to make forecasts. The following lemma shows that if the variable X_t is integrated of order 1 ($X_t \sim I(1)$), conditional forecasts of this variable over arbitrary forecasting horizons i (i.e., $E_t X_{t+i}$) contain a unit root. For instance, if stock price is an I(1) process, 1-year ahead forecasts of stock prices also contain a unit root.

Lemma 1 *If X_t follows (1)-(5) (i.e., $X_t \sim I(1)$), $E_t X_{t+i} \sim I(1)$ for $i > 0$.*

Proof See Appendix D. □

Then, we can establish the cointegration relationship among forecasts of different variables when their realizations are cointegrated. Suppose $y_t = \left(y_{1,t}\ y_{2,t}\ \ldots y_{n,t}\right)'$ is a $n \times 1$ vector which is cointegrated with cointegrating vector $a = (a_1\ a_2 \ldots\ a_n)'$ and

[6] Specifically, $\widetilde{\phi}(L) = \widetilde{\phi}_1 L + \widetilde{\phi}_2 L^2 + \cdots + \widetilde{\phi}_{\widetilde{p}} L^{\widetilde{p}}$, $\widetilde{\psi}(L) = \widetilde{\psi}_1 L + \widetilde{\psi}_2 L^2 + \cdots + \widetilde{\psi}_{\widetilde{q}} L^{\widetilde{q}}$, $\widehat{\phi}(L) = \widehat{\phi}_1 L + \widehat{\phi}_2 L^2 + \cdots + \widehat{\phi}_{\widehat{p}} L^{\widehat{p}}$ and $\widehat{\psi}(L) = \widehat{\psi}_1 L + \widehat{\psi}_2 L^2 + \cdots + \widehat{\psi}_{\widehat{q}} L^{\widehat{q}}$.

$a'y_t$ is a stationary process (with possibly time-varying volatility). Mathematically,

$$(1-\phi(L))a'y_t = (1+\psi(L))\,\sigma_{\eta,t}\eta_t,$$
$$(1-\widehat{\phi}(L))\left(\sigma^2_{\eta,t}-\overline{\sigma}^2_{\eta}\right) = \left(1+\widehat{\psi}(L)\right)\widetilde{\eta}_t,$$

where the roots of $1-\phi(z)=0$ and $1-\widehat{\phi}(z)=0$ are within the unit circle. Under the assumption of FIRE, agents know this cointegration relationship. We firstly establish a preliminary result which says the forecasts of an I(1) variable X made at date t over an arbitrary horizon i (E_tX_{t+i}) are cointegrated with X_k with cointegrating vector $(1,-1)$, where k can be identical to or different from t.

Lemma 2 *If X_t follows (1)-(5) (i.e., $X_t \sim I(1)$), $E_tX_{t+i}-X_k \sim I(0)$ for $i>0$.*

Proof See Appendix D. □

Denote by $E_{i_1}y_{1,i_1+j_1}$ j_1−period ahead expectation of variable y_1 made at date i_1.

Theorem 1 *If $a'y_t$ is a stationary process, $a_1E_{i_1}y_{1,i_1+j_1}+a_2E_{i_2}y_{2,i_2+j_2}+\cdots+a_nE_{i_n}y_{n,i_n+j_n}$ is stationary for arbitrary $i_1, i_2, \ldots i_n, j_1, j_2, \cdots, j_n > 0$.*

Proof See Appendix D. □

The theorem contains a rich set of testable implications for expectation formation.[7] For illustration, consider the asset pricing models in which realized stock prices and consumption are cointegrated with cointegrating vector $(1,-1)$ (e.g., the long-run risk model and habit model). First, a special case of the theorem is that forecasts of stock prices and consumption made at the same date (i.e., $i_1=i_2=\cdots=i_n$) and over the same forecasting horizons (i.e., $j_1=j_2=\cdots=j_n$) are cointegrated. And forecasts of stock price consumption ratio, i.e., $\left(E_t\log P_{t+j}-E_t\log C_{t+j}\right)$, are stationary. This means, for example, 1-year ahead forecasts of stock prices and 1-year ahead forecasts of consumption (made at the same date) are cointegrated with cointegrating vector $(1,-1)$.

Second, the cointegration relation holds for forecasts of different variables *over different forecasting horizons* (i.e., $j's$ need not to be identical) as ($E_t\log P_{t+j_1}-E_t\log C_{t+j_2}$) is stationary for $j_1\neq j_2$. This means, for instance, 10-year ahead forecast of stock prices and 1-year ahead forecast of consumption made at the same date are cointegrated. This result is particularly useful when the forecasting horizons of expectation data available to researchers are different across different variables. For instance, researchers may have data on 10-year ahead forecasts of stock prices and 1-year ahead (but not 10-year ahead) forecasts of consumption.

Third, the cointegration relation also holds for forecasts of different variables *made at different dates* (i.e., $i's$ need not to be identical) as ($E_{i_1}\log P_{i_1+j1}-E_{i_2}\log C_{i_2+j_2}$) is stationary for $i_1\neq i_2$. This means, for instance, stock price forecasts made during

[7] Researchers can apply these results to test the cointegration between forecasts of exogenous variables and forecasts of endogenous variables in their models. Moreover, they can study the cointegration between forecasts of different endogenous variables.

1960 − 1990 (over an arbitrary forecasting horizon) are cointegrated with consumption forecasts made during 1970 − 2000 (over an arbitrary forecasting horizon). This result is useful when the sample period of expectation data available to researchers is different (or do not exactly overlap) across different variables.

3.2 Stock pricing models with FIRE

We discuss the testable implications for stock price expectations in FIRE asset pricing models. For illustration, we firstly consider the long-run risks model studied in Bansal et al. (2012) with reproducing several model equations. Those equations will also be referred and useful for the analysis of the models which relax the FIRE assumption later.

The representative agent with recursive preferences maximizes his life-time utility given by

$$V_t = [(1-\delta)C_t^{\frac{1-\gamma}{\theta}} + \delta(E_t[V_{t+1}^{1-\gamma}])^{\frac{1}{\theta}}]^{\frac{\theta}{1-\gamma}}. \tag{6}$$

The variable θ is defined as $\theta \equiv \frac{1-\gamma}{1-1/\psi}$ where the parameters γ and ψ represent relative risk aversion and the elasticity of intertemporal substitution. Log consumption c_t and dividend d_t have the following joint dynamics

$$\Delta c_{t+1} = \mu_c + x_t + \sigma_t \eta_{t+1}, \tag{7}$$

$$x_{t+1} = \rho x_t + \varphi_e \sigma_t e_{t+1}, \tag{8}$$

$$\sigma_{t+1}^2 = \overline{\sigma}^2 + \nu(\sigma_t^2 - \overline{\sigma}^2) + \sigma_w w_{t+1}, \tag{9}$$

$$\Delta d_{t+1} = \mu_d + \phi x_t + \pi \sigma_t \eta_{t+1} + \varphi \sigma_t u_{d,t+1}. \tag{10}$$

$\mu_c + x_t$ is the conditional expectation of the growth rate of aggregate consumption. x_t is a persistent component, which captures long run risks in consumption and drives both the consumption and dividend process. ϕ captures a levered exposure of dividend to x_t. In addition, the i.i.d consumption shock η_{t+1} is allowed to influence the dividend process. It serves as an additional source of risk premia and π governs the magnitude of this influence.

Their paper provides the analytical solution for (log) price-consumption (dividend) ratio

$$\log\left(\frac{P_t}{C_t}\right) = A_0 + A_1 x_t + A_2 \sigma_t^2, \tag{11}$$

$$\log\left(\frac{P_t}{D_t}\right) = A_{0,d} + A_{1,d} x_t + A_{2,d} \sigma_t^2, \tag{12}$$

where A_0, A_1, A_2, $A_{0,d}$, $A_{1,d}$, $A_{2,d}$ are all constants and functions of model parameters, see their p. 189. Stock prices and aggregate consumption (dividend) are cointegrated, as x_t and σ_t^2 are stationary.

Using the US data, Appendix B tests whether *realized* aggregate stock price indices are cointegrated with fundamentals (aggregate consumption, dividends, and output).

We find that the testing outcomes broadly support the implication of the long-run risks model that realized stock prices are cointegrated with fundamentals.

Theorem 1 provides new testable implications for these FIRE asset pricing models. Given that the realized prices and fundamentals are cointegrated as in equation (11) and (12) and agents possess the knowledge of the equilibrium pricing function, they use this knowledge to forecast stock prices. Thus, the forecasts of stock prices and fundamentals are cointegrated. More precisely, agents' stock price forecasts $E_i \log P_{i+j}$ are cointegrated with their forecasts of aggregate consumption $E_k \log C_{k+l}$ (dividend $E_k \log D_{k+l}$) with cointegrating vector $(1, -1)$ for arbitrary $i,\ j,\ k,\ l > 0$. It is worth noting that this cointegration relationship exists even if the two forecasts are made at different dates and/or over different horizons.

In many other FIRE asset pricing models, including the endowment economy models (Campbell and Cochrane 1999) and general equilibrium models (Jermann, 1997; Boldrin et al. 2001; Croce 2014), realized stock prices and fundamentals are cointegrated. Theorem 1 implies a cointegrated relationship between forecasts of stock prices and fundamentals in those models, as a consequence of agents' knowledge of the equilibrium pricing function.

4 Cointegration restrictions on forecasts in Bayesian RE models

A large literature of asset pricing models deviates from FIRE and introduces subjective beliefs. The standard approach resorts to Bayesian RE modeling, which allows for subjective beliefs about fundamentals, while keeping the assumption that investors know the equilibrium pricing function linking stock prices to (beliefs about) fundamentals. Adam et al. (2017) dub this literature Bayesian RE models. We consider three such Bayesian RE models which incorporate consumption learning, or heterogeneous beliefs, or consumption sentiment.[8] It may not be straightforward whether the forecasts of stock prices and fundamentals are still cointegrated in the Bayesian RE models. This section examines those models individually.

4.1 Learning about consumption dynamics

One way to deviate from the FIRE assumption in asset pricing modeling is assuming that agents have incomplete information and learn about the exogenous consumption process, such as in Collin-Dufresne et al. (2016). In this type of learning models, agents know the equilibrium pricing mapping. Suppose the representative agent's preferences are represented by the Epstein-Zin utility (6). For illustration, the consumption process is

$$\Delta c_{t+1} = \mu_c + \overline{\sigma}\eta_{t+1}, \tag{13}$$

where η_{t+1} is an i.i.d process. Agents do not know the consumption growth rate but know the constant variance $\overline{\sigma}^2$. Agents learn μ_c over time and beliefs about μ_c is updated by

[8] Due to space limits, we discuss consumption sentiment models in Appendix C.

$$\mu_{c,t} = \mu_{c,t-1} + g_t \left(\Delta c_t - \mu_{c,t-1} \right). \tag{14}$$

Assuming constant gain or Kalman filter learning (under steady state variance ratio) is used, i.e., $g_t = g \in (0, 1)$. Substituting (13) into (14) yields $\mu_{c,t} = (1-g)\mu_{c,t-1} + g\,(\mu_c + \overline{\sigma}\eta_t)$, which is a stationary process.

Proposition 1 *Given the beliefs (13), agents' forecasts of stock prices* $E_i \log P_{i+j}$ *are cointegrated with their forecasts of aggregate consumption* $E_k \log C_{k+l}$ *with cointegrating vector* $(1, -1)$ *for arbitrary* $i,\ j,\ k,\ l > 0$.

Proof See Appendix D. □

Note that Proposition 1 holds even if stock price forecasts and consumption forecasts are made on different dates and/or over different forecasting horizons. While consumption growth forecasts appear to be non-rational, incorporating this feature alone into asset pricing models cannot break the cointegration relations between stock price forecasts and consumption forecasts.

4.2 Heterogeneous beliefs

So far we have analyzed representative agent asset pricing models with or without FIRE. Some papers deviate from FIRE by introducing heterogeneous agents, especially heterogeneous beliefs, e.g., Ehling et al. (2018) (EGH henceforth). Can *a deviation from the representative agent assumption and introducing heterogeneous beliefs* break the cointegration relationship between stock price forecasts and consumption forecasts? This section shows that models with heterogeneous beliefs and a willingness to "agree to disagree" do not necessarily break this. In these models, all agents can deduce and agree on the equilibrium pricing function and state-contingent stock prices. This knowledge usually requires strong informational assumptions. For instance, all agents' beliefs about fundamentals and preferences, etc are common knowledge.

Consider the model of EGH, which is a continuous-time overlapping generations economy. They study asset prices and portfolio choice by incorporating agents' learning from own experience about output process in a dynamic complete market setting. There are different cohorts who are born at different times and have heterogeneous beliefs about fundamentals, i.e., exogenous aggregate output process Y_t. The true process for Y_t is $dY_t/Y_t = \mu_Y dt + \sigma_Y dz_t$, where z_t is a standard Brownian motion. Agents disagree on this process and perceive that

$$dY_t/Y_t = \hat{\mu}_{s,t} dt + \sigma_Y dz_{s,t},$$

where the subscript s represents the cohort born at time s, $\hat{\mu}_{s,t}$ agents' perceived output growth rate, and $z_{s,t}$ denotes a Brownian motion under the belief of an agent born at time s. Agents know the standard deviation of output σ_Y.

Denote by $E_i^s \log P_{i+j}$ stock price forecasts made by cohort s at time i and over horizon j; similarly notations for the forecast of aggregate consumption $E_k^s \log C_{k+l}$.[9]

[9] S_t stands for stock prices. Here we use a different notation P_t.

It can be shown that in the EGH model, every individual's stock price forecast $E_i^s \log P_{i+j}$ is cointegrated with own forecasts of consumption $E_k^s \log C_{k+l}$ with cointegrating vector $(1, -1)$ for arbitrary $i, j, k, l > 0$. Therefore, the mean stock price forecasts across all agents made at time i and over horizon j, $\overline{E}_i \log P_{i+j}$ is cointegrated with the mean forecasts of aggregate consumption made at time k and over horizon l, $\overline{E}_k \log C_{k+l}$.

Proposition 2 *In the EGH model, the mean stock price forecasts across all agents* $\overline{E}_i \log P_{i+j}$ *is cointegrated with the mean consumption forecasts* $\overline{E}_k \log C_{k+l}$ *with cointegrating vector* $(1, -1)$ *for arbitrary* $i, j, k, l > 0$.

Proof See Appendix D. □

In addition, although agents have heterogeneous beliefs about consumption (or output), the knowledge of the equilibrium pricing function still implies that stock price forecasts made by every individual is cointegrated with her aggregate consumption (or output) forecasts. We will test this implication using the individual-level survey forecast data in Sect. 7.

5 Overview of the survey evidence

Before moving to the empirical part of the paper, Table 1 provides an overview of the survey evidence documented in the paper. The survey evidence is produced by employing multiple widely used survey forecast datasets, such as the Livingston Survey, Shiller Survey, Duke CFO Global Business Outlook survey, Survey of Professional Forecasters, and I/B/E/S forecasts. The participants of the surveys include market investors, analysts, CFOs, and professional economists from industry, government, banking, and academia.

The empirical findings are organized into three categories. The first category (Panel A) utilizes consensus (or average) forecasts across survey participants, such as median or mean forecasts. To assess the modeling of stock price expectation formation, these consensus forecasts serve as proxies for the forecasts of the representative agent (as in representative agent asset pricing models) or as the averages of forecasts across various agents (as in models with heterogeneous agents or beliefs). Importantly, we demonstrate that median (or mean) survey forecasts of aggregate stock price indices are not cointegrated with median (or mean) forecasts of aggregate consumption or dividends, contrary to the predictions of these representative agent or heterogeneous agents models. This evidence remains robust across various sources of expectations data, different forecasting horizons (1-quarter, 2-quarter, 4-quarter, and 10-year ahead), and with or without imposing the theoretically implied cointegrating vectors.[10] Additionally, we show that in these models, stock price forecasts over certain forecasting horizons are cointegrated with forecasts of fundamentals made at different dates and/or over

[10] Furthermore, the results are robust to the application of different statistical tests, such as Phillips-Perron test (Phillips and Perron 1988), Dickey-Fuller Generalized Least Squares (DF-GLS) test, KPSS test, and Johansen test as well as the use of median or mean forecasts for testing.

Table 1 Main evidence from survey forecasts: roadmap

Panel A: *Median/mean forecasts*	
Integration properties of forecasts of P, C, and D	Evidence A.1– A.5
No cointegration between P and C with imposing vector $(1, -1)$	Evidence 1, A.6
No cointegration between P and D with imposing vector $(1, -1)$	Evidence 2
No cointegration between P and C without imposing any vector	Evidence A.7, A.8
No cointegration between P and D without imposing any vector	Evidence A.9
Panel B: *Individual-level forecasts*	
No cointegration between P and Y over the same horizon with imposing $(1, -1)$	Evidence 3
No cointegration between P and Y over different horizons with imposing $(1, -1)$	Evidence A.10
No cointegration between P and Y over the same horizon without imposing any vector	Evidence A.11
No cointegration between P and Y over different horizons without imposing any vector	Evidence A.12
Panel C: *Additional several testing issues*	
Structural break	
Testing structure break in median/mean P/C ratios	Evidence A.13
No cointegration between median/mean P and C assuming a structure break	Evidence A.14
Testing structure break in P/D ratios	Evidence A.15-1
No cointegration between P and D assuming a structure break	Evidence A.15-2
Testing structure break in individual-level P/Y ratios	Evidence A.16-1
No cointegration between individual-level P and Y assuming a structure break	Evidence A.16-2
Sample size	
Recursive Johansen trace test for P and D (or P and C)	Evidence A.17
No cointegration between P and C made at different dates	Evidence A.18
No cointegration between P and C from a Monte Carlo study	Evidence A.19
Multiple testing problem	
No cointegration between individual-level P and Y adjusted for multiple testing	Evidence A.20
Individual-level panel cointegration test	Evidence A.21

Note: P, Y, C, and D stand for stock price, aggregate output, consumption and dividend, respectively
[a] Evidence with a label starting with "A" is presented in the Appendix

different horizons.[11] Guided by this result, we then demonstrate the absence of cointegration between survey stock price forecasts and fundamental forecasts when we combine forecasts of stock price and fundamentals made on different dates and over different horizons, contrary to the model predictions.

The second category of evidence (Panel B) utilizes individual-level survey forecast data (forecasts made by individual agent). These data provide an additional and direct test of the implications of stock pricing models with heterogeneous beliefs, complementing the test using consensus forecast data mentioned earlier. By examining individual-level Livingston Survey forecast data, we find that, for all forecasters,

[11] This is a particularly useful result in the case of limited availability of survey forecasts data when the forecasting horizons of survey forecast data available to researchers are different across different variables.

their forecasts of aggregate stock price indices are not cointegrated with forecasts of aggregate output, which contradicts the predictions of the models.[12] The results remain robust across different forecasting horizons, various cointegration tests, and whether theoretically implied cointegrating vectors are imposed or not.

We take several econometric issues seriously and provide additional evidence to address these issues in the last category (Panel C). For instance, potential structural breaks may lead to a non-rejection of the null hypothesis that stock price forecasts are not cointegrated with forecasts of consumption or dividend. Moreover, a relatively small sample size may introduce bias in cointegration testing. Furthermore, when individual-level forecast data is used, testing many hypotheses separately and simultaneously may lead to false rejections of the null hypothesis (the multiple testing problem). Our empirical findings remain robust to these considerations.

6 Evidence from consensus forecast data

Using several widely used survey forecasts datasets, this section tests the implications of the asset pricing models for stock price forecasts. This section utilizes the data at the consensus level and the next section at the individual level. The consensus forecasts data enables us to test both representative agent models and models with heterogeneous beliefs. We firstly describe the survey forecast data and present the integration and cointegration properties of median (and mean) forecasts. Note that using the US data, Appendix B shows that *realized* stock prices are cointegrated with fundamentals (aggregate consumption, dividend and output).

6.1 Data

Three sources of survey forecasts of US aggregate stock price indices are used. The first source is the Livingston Survey managed by the Federal Reserve Bank of Philadelphia. The survey contains forecasts of S&P 500 index made by professional economists from industry, government, banking sector, and academia. The stock price forecast data is semi-annual and covers from 1952 to the second half of 2019. Two forecasting horizons are available: 2- and 4-quarter ahead. The second source is Robert Shiller's survey of individual investors. Stock price forecasts are measured by forecasts of the Dow Jones index and available at a quarterly frequency. The data covers from the first quarter of 1999 to the second quarter of 2015. Four forecasting horizons are available: 1-quarter, 2-quarter, 4-quarter, and 10-year ahead. The last source is the Duke CFO Global Business Outlook, a quarterly survey conducted by Duke University's Fuqua School of Business and CFO magazine from the last quarter of 2001 to the last quarter of 2018.[13] The survey collects business leaders' S&P 500 stock index forecasts over 4-quarter ahead. All survey forecasts of stock prices are deflated by

[12] Since consumption (dividend) forecasts are not available from the survey, we use forecasts of aggregate output instead. In many general equilibrium asset pricing models with production, stock price forecasts are cointegrated with output forecasts (Jermann 1998; Boldrin et al. 2001).

[13] Duke CFO survey does not have stock price forecasts in 2019.

forecasts of inflation rate obtained from the Survey of Professional Forecasters (SPF) conducted by the Philadelphia Fed. The forecasting horizons of inflation forecast data are 1- to 4-quarter ahead as well as 10-year ahead. We also report empirical results when inflation expectations from the Michigan Surveys of Consumers (MSC) are used to deflate forecasts in Table A.8 of Appendix F.[14]

The source of US aggregate consumption forecasts is the SPF forecasts of the chain-weighted real personal consumption expenditures. It is available at a quarterly frequency and from 1981 Q3 onwards. Four forecasting horizons are available: 1-, 2-, 3-, and 4-quarter ahead. SPF consumption forecasts data is provided with varying base years. Appendix A explains the rebasing of consumption forecast data. The 4-quarter-ahead forecasts of aggregate dividend is the constructed S&P 500 dividends from the Thomson Reuters Institutional Brokers Estimate System (I/B/E/S) by aggregating analyst forecasts for individual firms in the S&P 500 constructed by De La O and Myers (2021). Most results reported in the main text use median survey forecasts. Appendix F shows our results are robust to using the mean forecasts.

Before proceeding to the test results, we discuss two issues. First, survey data on expected stock returns are often criticized as being noisy and thus meaningless, or that people do not mean what they say, or that survey responses are strongly dependent on framing and language. Greenwood and Shleifer (2014) discusses and addresses these criticisms; see their Section 1.8. They show stock return forecasts from different surveys are highly correlated and provide evidence that investors act in line with their reported expectations.[15] Moreover, in our context, as long as the noises or measurement errors in survey forecast data are i.i.d or stationary (which is commonly assumed in the literature), they do not affect the integration and cointegration properties of the forecast data as well as our empirical findings.

Second, median (or mean) survey forecasts serve as proxies for the forecasts of the representative agent in models, following the literature, e.g., Eusepi and Preston (2011), Coibion and Gorodnichenko (2015), Piazzesi (2015), Kuang and Mitra (2016), and Adam et al. (2017). With this view, the median (or mean) stock price forecasts from surveys serve as proxies for stock price expectations of the representative agent. In line with a common practice in the literature, we use the median (or mean) stock price forecasts from one survey and the median (or mean) forecasts of fundamentals (aggregate consumption, output and dividend) from another survey to test the cointegration between the forecasts of the two variables implied in asset pricing models.[16]

[14] Since households are asked to predict 4-quarter-ahead inflation, we report cointegration results for 4-quarter-ahead stock price and fundamental forecasts. Results are robust for all tests considered.

[15] Giglio et al. (2021) also provide evidence addressing these criticisms and strongly supports the use of survey expectations data in macro-finance models.

[16] For instance, De La O and Myers (2021) mix the dividend forecasts from I/B/E/S and stock price forecasts from CFO and Livingston Survey to explore the variation in price-dividend ratios. Another example is Adam et al. (2017). They use the median (or mean) nominal stock price forecasts from the Shiller Survey and inflation forecasts from SPF and Michigan Survey of Consumers to compute the median (or mean) forecasts of real stock capital gains, which are then used as a proxy for forecasts of real stock capital gains made by the representative agent in their model.

Different forecasters across surveys can contribute to producing non-existence of a cointegration relationship between stock price forecasts and fundamental forecasts.[17] Two measures have been taken to address this issue. First, we find that the correlation coefficient between median stock price forecasts in the Livingston Survey and these in the Duke CFO survey (both forecasting the S&P 500 index) are very high and 0.90; the corresponding correlation coefficient using mean forecasts is 0.91. This may suggest that the differences in forecasts across surveys are relatively small.[18] Additionally, in Sect. 7, we provide empirical evidence using forecasts made by the same individual from the same survey, which is not contaminated by this issue.

6.2 No cointegration between consensus forecasts of stock prices and fundamentals

This section studies the integration and cointegration properties of forecasts of the aggregate stock price index and aggregate fundamentals (aggregate consumption and dividend).

Integration property of the forecasts. We first test the integration properties of forecasts. Appendix E reports testing results for (median and mean) forecasts of stock price, aggregate consumption, and dividends over different horizons. The testing results suggest that forecasts of stock prices, aggregate consumption and dividend are I(1) but not I(2) processes, consistent with typical FIRE stock pricing models (e.g., the long-run risks model).

No cointegration when imposing theoretical restrictions. In the FIRE and Bayesian RE asset pricing models discussed in Sects. 3 and 4, stock price forecasts and consumption (or dividend) forecasts are found to be cointegrated with a cointegrating vector of (1, -1). This holds true regardless of whether the two forecasts are made on the same or different dates or over the same or different horizons. These models imply, for instance, 1-quarter ahead forecasts of stock prices are cointegrated with 1-quarter ahead forecasts of aggregate consumption (or dividend), and 4-quarter ahead forecasts of stock prices are cointegrated with 1-quarter ahead forecasts of consumption (or dividend).

Table 2 reports the test results on whether median forecasts of aggregate consumption are cointegrated with median forecasts of stock prices made at the same date and over the same or different forecasting horizons (with cointegrating vector (1, -1)). The last column of Panel A and B, labeled as "4Q P & 1Q C", test cointegration between 4-quarter ahead stock price forecasts and 1-quarter ahead consumption forecasts. In Panel C, the forecast horizon of CFO stock price is 4-quarter ahead, and the forecast horizons of SPF consumption are 1-, 2-, 3-, and 4-quarter ahead. Both PP and DF-GLS tests show that we cannot reject the null hypothesis that stock price forecasts

[17] The literature finds that financial analysts have various incentives to provide biased forecasts, such as herding (e.g. Graham 2022; Lamont 2002; Ottaviani and Sørensen 2006), standing out from the crowd (e.g., Laster et al. 1999; Ottaviani and Sørensen 2006; Marinovic et al. 2013), or conficts of interest (e.g., Francis and Philbrick 1993; Hong and Kubik 2003; O'Brien et al. 2005; Lin and McNichols 1998).

[18] The same professional forecaster or her institution could participate in multiple surveys and the forecasting methods used by the participants of one survey could be similar to those used by the participants of another survey.

Table 2 Cointegration tests between median stock price forecasts and consumption forecasts with the cointegrating vector (1, −1)

Panel A: *Livingston stock price forecasts and SPF consumption forecasts*

Median	1Q ahead	2Q ahead	4Q ahead	4Q P & 1Q C
PP (Z_t test)	*n.a*	−2.136	−2.104	−2.098
10% critical value	*n.a*	−2.590	−2.590	−2.590
DF-GLS	*n.a*	0.002	−0.238	−0.245
10% critical value	*n.a*	−1.832	−1.817	−1.817
KPSS	*n.a*	0.453	0.219	0.219
5% critical value	*n.a*	0.146	0.146	0.146

Panel B: *Shiller stock price forecasts and SPF consumption forecasts*

Median	1Q ahead	2Q ahead	4Q ahead	4Q P & 1Q C
PP (Z_t test)	−2.070	−1.970	−2.108	−2.104
10% critical value	−2.594	−2.594	−2.594	−2.594
DF-GLS	−1.810	−1.701	−1.728	−1.743
10% critical value	−1.895	−1.895	−1.895	−1.895
KPSS	0.422	0.420	0.433	0.432
5% critical value	0.146	0.146	0.146	0.146

Panel C: *CFO stock price forecasts and SPF consumption forecasts*

Median	1Q ahead	2Q ahead	3Q ahead	4Q ahead
PP (Z_t test)	−2.494	−2.500	−2.498	−2.502
10% critical value	−2.593	−2.593	−2.593	−2.593
DF-GLS	−1.052	−1.050	−1.052	−1.055
10% critical value	−1.884	−1.884	−1.884	−1.884
KPSS	0.617	0.617	0.617	0.616
5% critical value	0.146	0.146	0.146	0.146

Evidence 1: Median stock price forecasts and consumption forecasts are not cointegrated with the vector (1, −1)

are not cointegrated with consumption forecasts with cointegrating vector (1, -1) at the 10% significance level, robust to different data sources and forecasting horizons, while KPSS test shows that the null hypothesis of cointegration between stock price forecasts and consumption forecasts is rejected at the 5% significance level.[19] The same conclusion is reached with mean forecasts, see Table A.9 in Appendix F.

No cointegration without imposing theoretical restrictions. Additionally, we perform cointegration tests between forecasts of stock prices and aggregate consumption (or dividend) without imposing the theory-implied cointegrating vector (1, -1), using the Engle–Granger (EG) test. Test results are reported in Appendix Tables A.10 and A.11 for median and mean stock price forecasts and consumption forecasts, respectively. Results for forecasts of stock price forecasts and dividends forecasts are shown

[19] For the DF-GLS test, since we report the test statistics and critical values with the number of lags that minimize the modified AIC criterion, the critical value for different tests differ.

Table 3 No cointegration between stock price forecasts and dividend forecasts with the cointegrating vector $(1, -1)$

CFO stock price forecasts and I/B/E/S dividend forecasts		
	Median	Mean
PP (Z_t test)	−1.901	−1.918
10% critical value	−2.600	−2.600
DF-GLS	−2.827	−2.877
10% critical value	−2.886	−2.886
KPSS	0.272	0.271
5% critical value	0.146	0.146

Evidence 2: Median (and mean) dividend forecasts and stock price forecasts are not cointegrated

in Appendix Table A.12. To sum up, we do not find cointegration relationship between *consensus* forecasts of stock prices and aggregate fundamentals (aggregate consumption or dividend), contrary to the predictions of the asset pricing models discussed in Sect. 3 and 4.

7 Evidence from individual forecasts

This section presents new survey evidence testing the implications of the asset pricing models using individual-level forecasts data. Compared to Sect. 6, the advantage of using individual expectations is that both the expectations of aggregate stock price indices and aggregate output come from the same individual, thus avoiding the issue of using forecasts from different surveys.

7.1 Data

The Livingston survey provides stock price index forecasts and output forecasts made by individual forecasters. Two forecasting horizons are available: 2-quarters and 4-quarters ahead. This allows us to examine the cointegration between individual-level stock price forecasts and output forecasts, that is, the stock price forecasts and output forecasts made by the same individual.[20] Typically, stock prices and output share a common trend driven by a unit-root productivity process and are cointegrated with each other, as demonstrated in production-based asset pricing models (Jermann 1998; Boldrin et al. 2001). To test whether stock price forecasts are cointegrated with output forecasts at the individual level, we focus on individuals with more than 50 observations. Figure 1 displays the IDs of individual forecasters and the corresponding number of observations for each ID. Real stock price forecasts are derived by adjusting survey stock price forecasts using the same individual's inflation forecasts. Survey output forecasts are similarly adjusted, as explained in Appendix A.

[20] The Livingston survey asks respondents their forecasts of aggregate output but not forecasts of consumption or dividend. Thus, we do not have forecasts of stock prices and forecasts of consumption or dividend from the same individual.

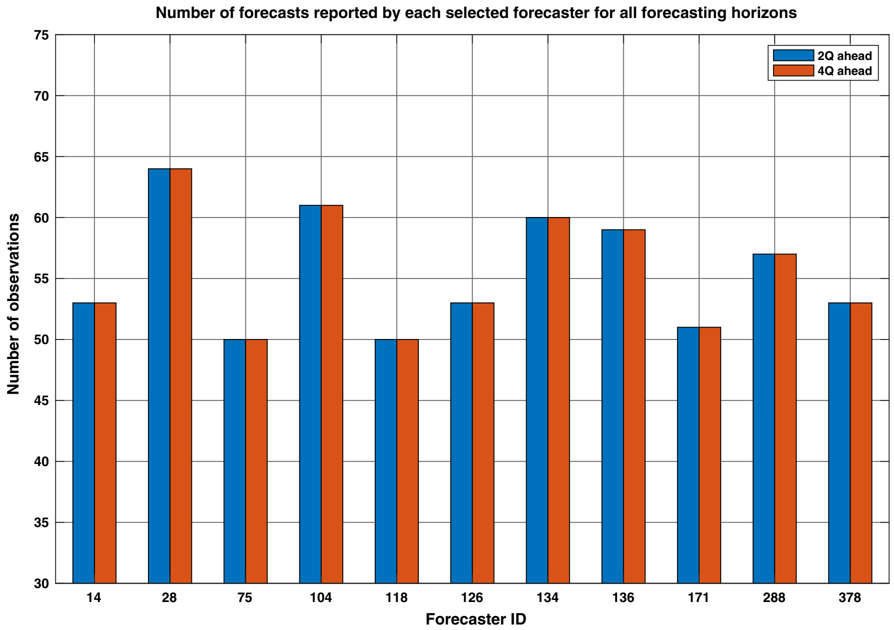

Fig. 1 Number of Livingston survey forecasts reported by each selected forecaster for 2- and 4-quarter ahead forecasting horizons

7.2 No cointegration between individual-level stock price forecasts and aggregate output forecasts

No cointegration between forecasts over the same horizon. We first test the cointegration relationship between individual-level aggregate output forecasts and aggregate stock price forecasts over the same horizon while imposing the theory-implied (1, -1) cointegrating vector.[21] Figures 2 and 3 visualize the test statistics against the corresponding critical values obtained from PP, DF-GLS, and KPSS tests, using forecasts from 11 forecasters for both the 2-quarter and 4-quarter horizons, respectively. The test statistics are represented by the circles at the end of each red line, while the corresponding critical values are indicated by the blue lines. Forecaster IDs are displayed on the x-axis.

For all forecasters, the test statistics of all three tests consistently exceed the critical values in all cases. These results generally suggest the absence of cointegration between stock price forecasts and output forecasts at the individual level.

No cointegration between forecasts over different horizons. Appendix Figure A.1 (or A.2) presents the test results generated by the PP, DF-GLS, and KPSS tests, using 2-quarter (or 4-quarter) ahead stock price forecasts and 4-quarter (or 2-quarter) ahead aggregate output forecasts from the 11 forecasters. These results suggest that,

[21] We find that individual forecasts of stock prices and output are I(1) processes but not I(2) process and do not report them here due to space limitation.

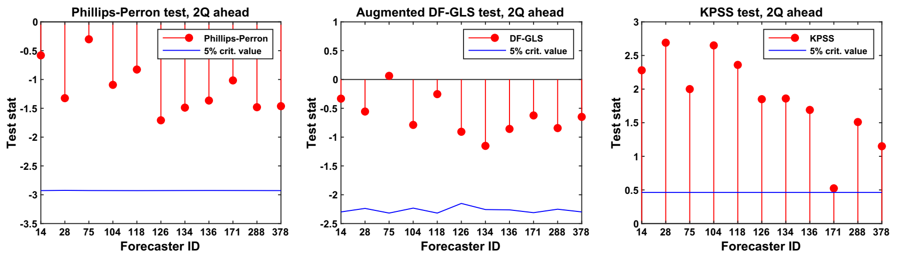

Fig. 2 Cointegration tests between 2Q-ahead individual-level forecasts of stock prices and output

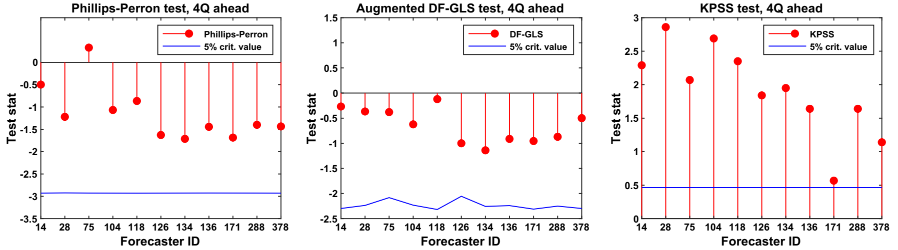

Fig. 3 Cointegration tests between 4Q-ahead individual-level forecasts of stock prices and output. Evidence 3: Individual stock price forecasts and output forecasts over the same horizon are not cointegrated with the vector (1, -1)

for all forecasters, there is no cointegration between stock price forecasts and output forecasts across different time horizons.

No cointegration without imposing theoretical restrictions. Furthermore, we test the cointegration properties of individual-level forecasts without imposing theoretical restrictions. Appendix Figures A.3 and A.4 indicate that individual-level stock price forecasts and aggregate output forecasts, whether made over the same or different horizons, are not cointegrated.

8 Several testing issues

This section considers and addresses several issues of econometric testing.

8.1 Structural breaks

The results so far have not considered potential structural breaks in the sample. A concern is that a structural break may lead to the non-rejection of no cointegration between the forecasts. To address this concern, this section employs the Recursive Cusum test (Ploberger and Krämer (1992); Brown et al. (1975)) and the Gregory and Hansen (1996) cointegration test.

Recursive Cusum tests for forecasts of stock price and consumption. The Recursive Cusum test examines parameter stability with the null hypothesis of no structural break. The test statistics assess whether the time series undergoes abrupt changes that are not predicted by the model across rolling samples. Table A.13 in Appendix H displays the Recursive Cusum test statistics alongside the corresponding 5% critical values, assuming OLS residuals for forecasts of stock price-consumption ratios. All of the test statistics are below their respective critical values, suggesting that the Recursive Cusum tests indicate no structural break is present in the estimated coefficients obtained from the augmented DF regression. Consistent results using mean forecasts are reported in Table A.14 in Appendix H. Similar results, obtained with recursive residuals, are not included here for the sake of brevity.

Gregory-Hansen tests for forecasts of stock price and consumption. For robustness, we also employ the Gregory-Hansen test to investigate potential structural breaks. The null hypothesis of this test assumes the presence of a structural break and no cointegration at the break point. Rejecting the null hypothesis implies the existence of a cointegration relation with a structural break. Table A.15 in Appendix H reports the Gregory–Hansen test statistics and the corresponding critical values. The null hypothesis is not rejected for all combinations of stock price and consumption forecasts. This suggests that there is no cointegration between these two forecasts, even when accounting for a structural break. Test results using mean forecasts are consistent and are reported in Table A.16 in Appendix H.

Tests for stock price and dividend forecasts. Table A.17 in Appendix H presents the results of structural break tests for median and mean forecasts of stock price-dividend ratios. Panel A of the Recursive Cusum test indicates the absence of a structural break in the estimated coefficients. Additionally, the results of the Gregory–Hansen test suggest no cointegration between stock price forecasts and dividend forecasts when assuming the existence of a structural break.

Tests for individual-level forecasts. Similarly, as demonstrated in Figure A.5 and A.6 in Appendix H, the results remain robust when considering structural breaks in individual forecasts. The Recursive Cumsum tests indicate that all individual forecast data reject the presence of a structural break. Furthermore, the Gregory-Hansen test suggests that, taking into account a structural break, there is no cointegration between stock price forecasts and output forecasts for almost all individuals.

8.2 Sample size

The paper uses some of the most powerful tests like the DF-GLS tests.[22] Moreover, to avoid the concern about the power of those tests, we apply the KPSS test which tests the null hypothesis of a stationary process against the alternative of a unit root. This section addresses the small sample issue in three additional ways. The first is examining the effects of sample size through recursive trace tests. Figure A.7 in Appendix H plots the test statistics (red lines) and corresponding 5% critical values (blue lines) of recursive Johansen trace test with rank = 0 for the CFO forecasts of stock price and I/B/E/S dividend forecasts. Figures A.8 - A.11 in Appendix H plot the test statistics (red

[22] The power of the standard Dickey-Fuller class of unit root tests was frequently criticized in the 1980 s and 1990 s, e.g., Cochrane (1991, 1994). Subsequent work has made great advances in improving the power of the tests. Ng and Perron (2001) and Haldrup and Jansson (2006) argue some subsequently developed tests have much improved or excellent power.

lines) and corresponding 5% critical values (blue lines) of recursive Johansen trace test with rank = 0 for median and mean Livingston, Shiller, and CFO forecasts of stock price and SPF consumption forecasts, respectively. All test statistics are below the corresponding critical values, and the test statistics do not increase monotonically with sample size.[23]

Second, Theorem 1 and Proposition 1 - 3 imply that stock price forecasts $E_{i_1} \log P_{i_1+j_1}$ and consumption forecasts $E_{i_2} \log C_{i_2+j_2}$ are cointegrated in the FIRE and Bayesian RE models when the two forecasts are made on different dates ($i_1 \neq i_2$). This allows us to enlarge the sample size for testing using the Livingston survey. In Panel A of Table A.18 in Appendix H, we test cointegration between Livingston median stock price forecasts with $i_1 = 57\text{H}1, 57\text{H}2, \ldots, 19\text{H}2$ and SPF median consumption forecasts with $i_2 = 84\text{Q}1, 84\text{Q}2, 84\text{Q}3, \ldots, 15\text{Q}2$.[24] Similarly, we test cointegration when $i_1 = 57\text{H}1, 57\text{H}2, \ldots, 19\text{H}2$ and $i_2 = 87\text{Q}4, 88\text{Q}1, \ldots, 19\text{Q}1$ in Panel B and when $i_1 = 59\text{H}1, 59\text{H}2, \ldots, 19\text{H}2$ and $i_2 = 88\text{Q}4, 89\text{Q}1, \ldots, 19\text{Q}1$ in Panel C. Thus, the cointegration tests in Panel A and B utilize 126 pairs of observations, while the tests in Panel C use 122 pairs of observations. In each panel, four combinations of forecasting horizons are considered. PP, DF-GLS, and KPSS tests suggest no cointegration between stock price forecasts and consumption forecasts made on different dates. Hence, a larger sample does not lead to the rejection of no-cointegration.

Third, although we use the KPSS test to avoid potential power problem, the asymptotic distribution of the KPSS test may be biased in a small sample. We conduct a Monte Carlo study to address this issue. In the long-run risk model presented in Sect. 3.2, forecasts of $\log(P/C)$ are stationary, consistent with the null hypothesis of KPSS test. Assuming the long-run risk model is the true data-generating-process, we adopt Monte Carlo simulation to generate critical values of KPSS tests in a small sample. First, we obtain analytical expressions for 2- and 4-quarter-ahead forecasts of $logP$ and $logC$. Second, we simulate the long-run risk model with $N = 10,000$ repetitions and each sample matches the sample size and frequency of the Livingston survey data. We then obtain the KPSS statistics from each repetition and hence the distribution of statistics. The third row of Panel A (or B) in Table A.19 in Appendix H reports the corrected 5% critical values obtained from the Monte Carlo study. The simulated critical values do not change much. Using 2-quarter- (and 4-quarter-ahead) Livingston stock price forecasts and SPF consumption forecasts, the results still reject the null hypothesis of stationarity at the 5% significance level, robust to using median or mean forecasts data.

8.3 Multiple testing problem

Section 7 analyzed the cointegration relation between individual-level forecasts of stock price and output by performing multiple unit root (or cointegration) tests simultaneously. A concern is that the testing outcomes might be subject to the multiple

[23] Appendix H.2 shows that for individual forecasts data, the test statistics of recursive Johansen trace tests do not vary monotonically with the sample size.

[24] "57H1" stands for the forecast made in the first half of the year 1957 and "84Q1" the forecast made at the first quarter of the year 1984.

testing problem. This issue is addressed in two ways. First, we use Anderson's sharpened False Discovery Rate (FDR) q-values (Anderson 2008), which is a corrected version of p-values and has greater power than many other methods. Second, we perform a panel cointegration test that considers cross-sectional dependence, which utilizes a larger sample size and has higher power. Table A.20 in Appendix H.3 reports corrected PP testing outcomes for both forecasts of stock price-output ratios for 11 forecasters, using FDR sharpened q-values. It shows no cointegration between forecasts of stock price and output, even after considering the multiple testing problem.

Since these professional forecasters are exposed to common aggregate shocks, their forecasts may be highly correlated. We test the cross-sectional dependence of forecasts of stock price-output ratios across the forecasters, using the cross-sectional dependence test developed by Pesaran (2006, 2015). Table A.21 in Appendix H.3 reports the p-values and average correlation coefficients of the tests over several combinations of forecasting horizons. For instance, the test shows that the p-value for 2-quarter ahead stock price-output forecast ratio is 0.000 and the average correlation coefficient is 0.84. The cross-sectional dependence tests uniformly reject the null of cross-sectional independence for forecasts of stock price-output ratio over all combinations of horizons. And the average correlation coefficients are fairly close to 1, indicating the presence of high cross-sectional dependence in our panel forecast data.

First-generation panel unit root tests such as the Fisher-type panel tests generally ignore such instances of dependence and suffer from size distortions. To address this issue, we adopt a version of second-generation panel unit root tests, the cross-sectionally augmented Dickey–Fuller (CADF) test proposed by Pesaran (2007). It tests the unit root in heterogeneous panels with the null hypothesis that all panels are non-stationary, against the alternative hypothesis that at least one panel is stationary. The CADF test eliminates cross-sectional dependence by augmenting the Augmented Dickey–Fuller (ADF) regression with cross-sectional average lagged levels and the first differences of the individual data series.[25] Table A.22 in Appendix H.3 reports the p-values of the CADF panel unit root tests on forecasts of stock price-output ratios over different combinations of forecasting horizons. The tests uniformly fail to reject the null that all panels are non-stationary at any conventional significance level.

9 Discussion

Section 9.1 discusses the types of models which could replicate the evidence. Section 9.2 motivates why we model expectation formation in our stock pricing model by adding judgement in forecasting. Section 9.3 develops a stock pricing model which simultaneously replicates the new survey evidence and several main facts of stock pricing.

[25] All panel unit root tests are performed with Newey-West optimal lags. Test results are robust to different numbers of lags incorporated.

9.1 Implications for the modeling of stock price expectations

The survey evidence casts some doubt on the modeling of stock price expectation in models with FIRE or Bayesian RE in which stock price forecasts are cointegrated with forecasts of fundamentals in these models. The cointegration between the two forecasts in those models arise from agents' knowledge of the equilibrium pricing function. To reconcile the survey evidence, it appears natural and crucial to relax agents' knowledge of equilibrium pricing function.

Many models relax this knowledge of agents. One type of asset pricing models which do not assume this knowledge is adaptive learning models. Examples include Adam, Marcet and Beutel (2017, AMB), Carceles-Poveda and Giannitsarou (2008), Lansing (2010), Branch and Evans (2010, 2011), and Boswijk et al. (2007). In this type of models, each investor has imperfect knowledge of stock markets; she may not know other investors' preferences and stock price beliefs. Hence, she cannot deduce the equilibrium pricing function. Instead, she forms expectations about payoff-relevant variables, such as stock prices, by using a statistical forecasting model and constantly revising the parameters of her model. Equilibrium stock prices are used to revise expectations about future stock prices. In the spirit of this literature, we later develop a stock pricing model based on Adam, Marcet and Nicolini (, AMN) and AMB and shows it reconciles the survey evidence. As relaxing the knowledge of the equilibrium pricing function is necessary but insufficient to replicate this finding, we consider a modification of the modeling of stock price expectation, namely, adding a judgement component on top of model-based forecasts, motivated by the evidence discussed in the next section.

The adaptive learning models may not be regarded as the only way to reconcile the empirical findings. The empirical findings are potentially consistent with models with various behavioral biases that also relax the assumption of common knowledge about the equilibrium mapping. Bordalo et al. (2019) propose diagnostic expectation based on the representativeness heuristic to explain the joint dynamics of fundamentals, expectations, and returns of portfolios of stocks and they use diagnostic parameter θ to capture the distance from FIRE. If an agent has different diagnostic parameters for stock price and dividend, their stock price forecasts and dividend forecasts may not be cointegrated. Actually, Bordalo et al. (2020) show that the diagnostic parameter capturing the distance from FIRE differs across economic variables varying from 0.2 to 1.5. The different diagnostic parameters suggest that there is a lack of common knowledge of equilibrium pricing mapping. Thus, a model with diagnostic expectation could be consistent with our empirical evidence as well.

To relax the common knowledge assumption and replicate the survey evidence, another avenue of modeling is assuming that investors use different models to forecast macroeconomic variables versus financial variables. Forecasters may utilize macroeconomic models to forecast macroeconomic variables and financial models to predict stock prices (which may capture the common practice of professional forecasters). It is widely acknowledged that financial and macroeconomic models often lack consistency with each other. This may contribute to generate the non-existence of cointegration between forecasts of financial variables and macroeconomic variables in models and in reality.

Lastly, we discuss the relationship between the extrapolative belief literature (e.g., Greenwood and Shleifer 2014) and our evidence of the lack of long-run cointegration relationships between stock price forecasts and fundamental forecasts. These long-run relationships exist in some extrapolative belief models, such as the sentiment-based model detailed in Appendix C. However, these long-run relationships do not exist in some other models with extrapolative beliefs, such as the learning model developed in Sect. 9.3 and Appendix I as well as in models with diagnostic expectations. The existence of these long-run relationships depends on whether investors possess knowledge of the equilibrium pricing mapping from fundamentals to stock prices.

9.2 The role for judgement in expectation formation

This section motivates the modeling of expectation formation in our asset pricing model developed in the next section, namely, the use of judgement on top of model-based forecasts. Forecasting in reality nearly always means the use of judgement in addition to best-effort statistical analysis, as forecasters are aware of the deficiencies of their models and know that the models may not capture all economic effects. Post-estimation adjustments are naturally added to their forecasts. Reifschneider (1997) discuss how prominently judgement enters into actual macroeconomic forecasting.

Several central banks conducted special surveys on the forecasting methods and practice of professional forecasters, including the European Central Bank (ECB) and the Federal Reserve Bank of Philadelphia. Those surveys shed light on professional forecasters' expectation formation by uncovering a prominent role for judgement. For instance, the ECB conducted three such special surveys in 2008, 2013, and 2018. It finds that for over 80% of forecasters in each survey, the forecasts of inflation, output growth, and unemployment rate over short, medium and long horizons contain a judgement component, see the bottom panel of Chart A in de Vincent-Humphreys et al. (2019). In addition, the Real-Time Data Research Center of the Federal Reserve Bank of Philadelphia conducted a special survey in 2009, the SPF Panelists' Forecasting Methods, which explicitly asks participants their forecasting methods used to complete the SPF questionnaire. It finds that almost all respondents (20 of 25 respondents) add subjective judgement on top of the forecasts generated by a mathematical/computer model, see Stark (2020).

A number of papers have studied the role for adding judgement (or expectation shocks) in expectation formation in macroeconomic fluctuations and monetary policy design. For instance, Svensson (2003, 2005) study optimal monetary policy when the policymaker explicitly incorporates judgement that affects the forecasts of key economic variables and shows that this can improve economic performance. Bullard et al. (2008) examine the role of agents' judgemental adjustment to forecasts in New Keynesian models with learning. Milani (2011) estimated a New Keynesian model with learning and expectation shocks (judgement). They show that judgement may lead to self-fulfilling fluctuations in New Keynesian models.

9.3 A stock pricing model

To reconcile our survey evidence, we formally develop a stock pricing model by extending the models in AMN and AMB. In our model, investors are uncertain about how asset prices relate to economic fundamentals and do not know the equilibrium pricing function. They do not fully understand how market prices are formed, so that their subjective probability distribution about prices may not be exactly equal to the true equilibrium distribution. Agents nevertheless have a very good understanding of how to predict prices. Their beliefs about prices are near-rational in the sense that they are assumed to be close to the rational expectations equilibrium (REE) beliefs.

Consistent with the evidence discussed in the previous section, investors' stock price expectations are formed via a mathematical model plus subjective judgement. The latter component is absent in the models of AMN and AMB and assumed to be unrelated to the forecasts of fundamentals. Adding this component to investors' stock price forecasts is crucial for delinking the cointegration relation between stock price forecasts and fundamental forecasts and reconciling with the survey evidence.

We estimate the model with both fundamental shocks to consumption and dividend and judgement shocks. For moderate risk aversion, the model can simultaneously replicate our survey finding of no cointegration between stock price forecasts and fundamental forecasts as well as quantitatively account for equity pricing facts, such as the observed risk premium, high volatility of stock returns, and high persistence and volatility of the price-dividend ratio. We consider this approach as minimal deviation from the standard approach by assuming that agents act optimally based on a system of subjective beliefs that is internally consistent and closely aligned (though not identical) with RE beliefs, as highlighted in AMN and AMB. Due to space limitation, we relegate the full details of the model and quantitative estimation results into Appendix I.

Before conclusion, we provide a general discussion on estimating macroeconomic models and using them for policy or counterfactual analysis. We regard the standard RE model as an essential benchmark. However, we think it is crucial to take into account realistic expectation form processes in model analysis. Standard FIRE models that do not take expectations data into account might often lead to biased estimation and policy recommendations. For example, Campbell and Cochrane (1999) assume FIRE, which necessitates an unreasonably high level of risk aversion to reproduce stock market moments. By contrast, both AMN and our stock pricing model replicate realistic features of survey expectations data and stock market moments with a more realistic level of risk aversion. By estimating a monetary business cycle model with learning, Milani (2006) shows that learning reduces the need of assuming strong degrees of inflation indexation or habit formation as assumed in FIRE models and helps in generating endogenous persistence in inflation. Milani (2011) argues that expectation shocks explain roughly half of business cycle moments, whereas other structural shocks only explain the remaining half. Furthermore, Gibbs (2017) demonstrates that beliefs formed from multiple forecasting models can lead to multiple equilibria, necessitating more aggressive policies to maintain stability. Kuang and Mitra (2024) develop a model to study the mismeasurement of estimates of structural balance and the role of its interaction with fiscal austerity in the prolonged recession in the European Union in the wake of the 2007–08 global financial crisis. The model captures many aspects of data on the EU fiscal policymakers' beliefs and suggests that without policymakers' over-pessimism, Eurozone GDP would have been 4.5% higher in 2012. Thus, it's crucial to incorporate various empirical evidence to inform our modeling of expectation formation while avoiding arbitrary deviations from the standard model.

10 Conclusion

There is a substantial and rapidly expanding body of literature dedicated to enhancing our understanding of the nature and implications of economic agents' expectation formation. This understanding is vital, given the significant role expectations play in various economic decisions, especially financial ones. This paper makes a novel and two-fold contribution to this existing literature. On the one hand, we formally show that asset pricing models with the assumption of FIRE, incomplete information, or heterogeneous beliefs typically imply a large number of cointegration relationships between stock price forecasts and forecasts of fundamentals (aggregate output, consumption, and dividends).[26] These relationships emerge within the models due to agents' common knowledge of the equilibrium pricing function, which maps (forecasts of) fundamentals to asset prices.

On the other hand, by leveraging several widely used survey forecast datasets, it provides robust new evidence that contradicts those predictions of the models, both at the consensus and individual levels. The survey evidence casts some doubt on the modeling of expectation formation in these models. We argue that it appears natural and crucial to relax agents' knowledge of the equilibrium pricing function. This paper formally develops an asset pricing model that relaxes this knowledge and replicates the new survey evidence together with several stylized facts of stock pricing.

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[26] These include FIRE models (e.g., Campbell and Cochrane 1999; Bansal et al. 2012; Boldrin et al. 2001; Croce 2014) and "Bayesian RE" models; the latter include consumption learning models (Collin-Dufresne et al. 2016), consumption sentiment (Jin and Sui 2022), and "agree to disagree" heterogeneous beliefs models (Ehling et al. 2018).

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