Do Stock Price Forecasts Reflect Fundamental Forecasts: A Long-run Perspective*

Pei Kuang, Li Tang, Renbin Zhang, and Tongbin Zhang

November 7, 2022

Abstract

Standard rational expectations stock pricing models typically imply that agents use the long-run cointegration relation between stock price and fundamentals to forecast future stock prices. Do survey stock market forecasts support this implication? We find that survey stock price forecasts are not cointegrated with forecasts of fundamentals (aggregate consumption, dividend, and output) at the average and individual level. The findings are robust to addressing the multiple testing problem, small sample problem, and to allowing for structural break.

Keywords: Survey expectation, Asset pricing, Cointegration

JEL classifications: D84, G12, G17

---

*Author contact. Pei Kuang, University of Birmingham, p.kuang@bham.ac.uk, Tel: (+44) 0121 4145620. Li Tang, Department of Economics, Middlesex University London, email: l.tang@mdx.ac.uk. Renbin Zhang: Shandong University, zhang.renbin.ken@gmail.com. Tongbin Zhang, Shanghai University of Finance and Economics (SUFE), tongbin.zhang.econ@gmail.com, address: Shanghai University of Finance and Economics, Guoding Road 777, Shanghai, China. We are grateful to Paul Beaudry, Tony Cookson, Jordi Gali, Jian Li, Albert Marcet and many participants of seminars at UAB, SUFE, HKUST, Jinan University, Peking University, SED conference (St. Louis), CCER Summer Institute, Shandong University, Behavioral Macroeconomics Workshop (Bamberg), Econometric Society China Meeting (Guangzhou) and North American Summer Meeting (Seattle), Shanghai Macroeconomics Workshop, SNDE conference (Dallas Fed), Royal Economic Society annual conference 2021, International Symposium on Econometric Theory and Applications (Osaka University) for helpful comments.

1 Introduction

Expectations play a crucial role in financial markets and asset pricing. The demand of assets today depends on investors' expectations about future fundamentals and prices. The market price of assets therefore reflects investors' price and fundamental expectations. However, there is a large debate on how to model investors' expectations in stock markets (Adam and Nagel, 2022). Recent research employs survey expectations data to test and discipline the modeling of expectation formation in asset pricing, such as the rejection of rational expectations (Greenwood and Shleifer, 2014; Adam et al., 2017), the rejection of risk-neutral forecasts and ambiguity aversion (Adam et al., 2021), the important role of cash flow growth expectations in explaining stock price movements (De La O and Myers, 2021; Giglio et al., 2021).

Standard rational expectations (RE) models typically imply that stock prices are cointegrated with fundamentals (aggregate consumption, dividend, and output), e.g., Lucas (1978), Campbell and Cochrane (1999), Jermann (1998), Boldrin et al. (2001), and Bansal and Yaron (2004). As a consequence of RE, agents have this knowledge and incorporate it to forecast future stock prices. Formally, we show that those models impose a large number of cointegration restrictions between forecasts of stock prices and forecasts of fundamentals.

Do agents in reality make use of these restrictions to forecast future stock prices? Employing several widely used survey expectation datasets, the paper offers some new evidence on stock price expectations. Survey participants include market investors, professional economists, and chief financial officers (CFOs). Robust empirical findings suggest that survey forecasts of stock prices are not anchored by forecasts of macroeconomic fundamentals (consumption, dividend, and output) in US stock markets from a long-run perspective.

First, we show that median (or mean) survey forecasts of the aggregate stock price index are *not* cointegrated with median (or mean) forecasts of aggregate consumption or dividend.[1] Put differently, the long-run or trend component of stock price forecasts is not anchored by

[1]In the literature, the median (or mean) forecasts from expectations surveys is generally interpreted as a proxy for the forecasts of the representative agent in models (Piazzesi et al., 2015; Coibion and Gorodnichenko, 2015; Kuang and Mitra, 2016; Adam et al., 2017).

forecasts of consumption or dividend. This evidence is robust to different sources of expectations data (Livingston Survey, Shiller Survey, and CFO survey for stock price forecasts; Survey of Professional Forecasters for consumption forecasts; I/B/E/S dividend forecasts), forecasting horizons (1-quarter-, 2-quarter-, 4-quarter- and 10-year-ahead), statistical tests (Phillips-Perron test, Dickey-Fuller Generalized Least Squares (DF-GLS) test, KPSS test, and Johansen test), the use of median or mean forecasts for testing, and mixing and matching forecasts of stock price and fundamentals made on different dates and over different horizons for testing.

Second, individual forecasters can display significant heterogeneity, which is widely documented in the literature (Mankiw et al., 2003; Coibion and Gorodnichenko, 2012; Andre et al., 2021). Using the Livingston Survey, this paper provides cointegration testing results between individual-level stock price forecasts and output forecasts.[2] We find that almost all forecasters do not appear to use the cointegration relationship between stock prices and output in forecasting, as their forecasts of stock prices are not cointegrated with output forecasts. The results are robust to different cointegration tests. Table 1 provides a roadmap of the empirical findings.

A number of econometric issues are examined. 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. In addition, a small sample may produce a 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.

The evidence has implications for modeling expectation formation in stock markets. Standard RE stock pricing models typically assume that agents possess knowledge of the equilibrium pricing function (i.e., the equilibrium mapping from realization or forecasts of fundamentals to stock prices), which dictates a cointegration relationship between stock prices and fundamen-

[2]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).

tals.[3] This knowledge leads to the cointegration relation between stock price forecasts and fundamental forecasts in these models. To reconcile the survey evidence, it appears natural to relax the agents' knowledge of the equilibrium pricing function as is present in, e.g, adaptive learning models; examples include Carceles-Poveda and Giannitsarou (2008), Lansing (2010, 2019), Kuang (2014), Branch and Evans (2010, 2011), Boswijk et al. (2007), and Adam et al. (2017). Agents in these models have imperfect knowedge of stock prices and form subjective stock price expectations which could be delinked from fundamental forecasts.

This paper relates to recent work which utilizes survey expectations data to analyze empirically agents' expectation formation and its implications via economic models. A large literature provides evidence which appears difficult to replicate under the assumption of full-information RE, such as Greenwood and Shleifer (2014) and Adam et al. (2017) in the context of asset pricing and Branch (2004) and Coibion and Gorodnichenko (2015) in the context of inflation expectations. Beyond RE tests, Malmendier and Nagel (2011) show that investors'experience of macroeconomic outcomes affects their financial risk-taking decisions. Adam et al. (2021) empirically reject that survey return expectations are formed by risk-neutral investors or ambiguity averse/robust investors. Based on survey data (Malmendier and Nagel, 2011, 2016), Nagel and Xu (2022) build an asset pricing model with learning with fading memory about dividend process to replicate several stock market facts such as counter-cyclical risk premium. Bordalo el al. (2019) and Bordalo el al. (2020) find that forecasters typically over-react to their individual news, while consensus forecasts under-react to average news in terms of the forecasts of macroeconomic and financial variables. To reconcile the findings, they combine a diagnostic expectation model of belief formation with a noisy information model of belief dispersion. We contribute to the literature by focusing on a new dimension from a long-run perspective, i.e., the cointegration restrictions between economic forecasts. In a related paper, Kuang, Tang,

[3]Examples include full information rational expectations (RE) 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, Johannes and Lochstoer, 2016), consumption sentiment (Jin and Sui, 2018), and "agree to disagree" heterogeneous beliefs models (Ehling et al., 2018). The Bayesian RE models make an asymmetric assumption about fundamentals and prices: it is assumed that investors do not understand the behavior of fundamentals (like aggregate dividend or consumption) but investors understand perfectly well the equilibrium mapping from forecasts of fundamentals to current stock prices. Adam and Marcet (2011) show that these models usually make strong informational assumptions on agents.

Zhang and Zhang (2022) provide survey evidence that the majority of professional forecasters do not use long-run cointegration relationships to forecast macroeconomic variables.

Table 1: **Main evidence from survey forecasts: roadmap**

Panel A: Median/mean forecasts	
Integration properties of forecasts of P, C, and D	Evidence 1A, B, C
Cointegration between P and C with imposing vector $(1, -1)$	Evidence 2
Cointegration between P and D with imposing vector $(1, -1)$	Evidence 3
Cointegration between P and C without imposing any vector	Evidence 4
Cointegration between P and D without imposing any vector	Evidence 5
Panel B: Individual-level forecasts	
Cointegration between P and Y over the same horizon with imposing $(1, -1)$	Evidence 6A
Cointegration between P and Y over different horizons with imposing $(1, -1)$	Evidence 6B
Cointegration between P and Y over the same horizon without imposing any vector	Evidence 7A
Cointegration between P and Y over different horizons without imposing any vector	Evidence 7B
Panel C: Addressing several issues	
Structural break	
Testing structure break in median/mean P /C ratios	Evidence 8A
Cointegration between median/mean P and C assuming a structure break	Evidence 8B
Testing structure break in P /D ratios	Evidence 9A
Cointegration between P and D assuming a structure break	Evidence 9B
Testing structure break in individual-level P/Y ratios	Evidence 10A
Cointegration between individual-level P and Y assuming a structure break	Evidence 10B
Sample size	
Recursive Johansen trace test for P and D (or P and C)	Evidence 11
Cointegration between P and C made at different dates	Evidence 12
Cointegration between P and C from a Monte Carlo study	Evidence 13
Multiple testing problem	
Cointegration between individual-level P and Y adjusted for multiple testing	Evidence 14
Individual-level panel cointegration test	Evidence 15

Note: P, Y, C, and D stand for stock price, aggregate output, consumption and dividend, respectively.

The reminder of the paper is organized as follows. Section 2 develops new theoretical results for expectation formation in full-information RE models. Section 3 presents evidence from median and mean survey forecasts. Section 4 reports evidence from individual forecast data. Section 5 addresses several econometric issues. Section 6 concludes.

2 Cointegration restrictions on forecasts in RE models

Macroeconomic and financial 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 between stock prices and fundamentals (dividend or consumption), such as in Campbell and Cochrane (1999) and Bansal, Kiku and Yaron (2012). As a consequence of agents' knowledge under RE, the same cointegration relationship exists between forecasts of these variables. To formalize this observation, consider a variable $\{X_t\}$ from a RE model, such as (log) stock price or aggregate consumption, which is generally represented by

$$\begin{aligned} X_t &= X_t^P + X_t^C, && (1)\\ X_t^P &= \mu + X_{t-1}^P + \sigma_{\epsilon,t}\epsilon_t, && (2)\\ (1-\phi(L))X_t^C &= (1+\psi(L))\,\sigma_{\eta,t}\eta_t, && (3)\\ (1-\widetilde{\phi}(L))\left(\sigma_{\epsilon,t}^2 - \overline{\sigma}_\epsilon^2\right) &= \left(1+\widetilde{\psi}(L)\right)\widetilde{\epsilon}_t, && (4)\\ (1-\widehat{\phi}(L))\left(\sigma_{\eta,t}^2 - \overline{\sigma}_\eta^2\right) &= \left(1+\widehat{\psi}(L)\right)\widetilde{\eta}_t. && (5) \end{aligned}$$

This variable contains a unit root. The superscripts P and C stand for the permanent and cyclical component. ϵ_t, $\eta_t, \widetilde{\epsilon}_t$, 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 $\overline{\sigma}_\eta^2$. $\phi(L) = \phi_1 L + \phi_2 L^2 + ... + \phi_p L^p$ and $\psi(L) = \psi_1 L + \psi_2 L^2 + ... + \psi_q L^q$ where L is the lag operator. $\widetilde{\phi}(L)$, $\widetilde{\psi}(L)$, $\widehat{\phi}(L)$ and $\widehat{\psi}(L)$ are similarly defined.[4] 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.

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

2.1 Integration property of conditional forecasts

Given the assumption of RE and full information, 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. Given (1)-(5), we have $E_t X_{t+i} = E_t X^P_{t+i} + E_t X^C_{t+i} = \mu i + X^P_t + E_t X^C_{t+i}$. $E_t X_{t+i}$ is the sum of a unit root process and a stationary process and hence a unit root process. ∎

2.2 Cointegration among forecasts of different variables

This section establishes the cointegration relationship among forecasts of different variables when their realizations are cointegrated.[5] Suppose $y_t = (y_{1,t}\ y_{2,t}\ ...y_{n,t})'$ is a $n \times 1$ vector which is cointegrated with cointegrating vector $a = (a_1\ a_2\ ...\ a_n)'$ and $a' y_t$ is a stationary process (with possibly time-varying volatility). Mathematically,

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

where the roots of $1 - \phi(z) = 0$ and $1 - \widehat{\phi}(z) = 0$ are within the unit circle. Under RE, 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 ($E_t X_{t+i}$) 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., $X_t \sim I(1)$), $E_t X_{t+i} - X_k \sim I(0)$ for $i > 0$.*

[5] 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.

Proof. Let

$$\begin{aligned} E_t X_{t+i} - X_k &= \left(E_t X^P_{t+i} + E_t X^C_{t+i}\right) - X_t + (X_t - X_k) \\ &= \left(E_t X^P_{t+i} - X^P_t\right) + \left(E_t X^C_{t+i} - X^C_t\right) + (X_t - X_k) \\ &= \mu i + \left(E_t X^C_{t+i} - X^C_t\right) + (X_t - X_k). \end{aligned}$$

$(E_t X_{t+i} - X_k)$ is stationary as $E_t X^C_{t+i}$, X^C_t and $(X_t - X_k)$ are stationary. ■

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 3 *If $a'y_t$ is a stationary process, $a_1 E_{i_1} y_{1,i_1+j_1} + a_2 E_{i_2} y_{2,i_2+j_2} + ... + a_n E_{i_n} y_{n,i_n+j_n}$ is stationary for arbitrary $i_1, i_2, ...i_n, j_1, j_2, ..., j_n > 0$.*

Proof. Let

$$\begin{aligned} & \left[a_1 E_{i_1} y_{1,i_1+j_1} + a_2 E_{i_2} y_{2,i_2+j_2} + ... + a_n E_{i_n} y_{n,i_n+j_n}\right] \\ = & \left[\sum_{k=1}^{n} a_k \left(E_{i_k} y_{k,i_k+j_k} - y_{k,i_k}\right) + \sum_{k=1}^{n} a_k y_{k,i_k}\right] \\ = & \left[\sum_{k=1}^{n} a_k \left(E_{i_k} y_{k,i_k+j_k} - y_{k,i_k}\right) + \sum_{k=1}^{n} a_k y_{k,i_1} + \sum_{k=1}^{n} a_k \left(y_{k,i_k} - y_{k,i_1}\right)\right]. \end{aligned}$$

Note Lemma 2 implies $(E_{i_k} y_{k,i_k+j_k} - y_{k,i_k})$ is stationary for $k = 1, 2, ...n$. In addition, the cointegration of the vector y_t yields $\sum_{k=1}^{n} a_k y_{k,i_1}$ is stationary and $y_{k,t} \sim I(1)$ gives $(y_{k,i_k} - y_{k,i_1})$ is stationary. Thus, we have $a_1 E_{i_1} y_{1,i_1+j_1} + a_2 E_{i_2} y_{2,i_2+j_2} + ... + a_n E_{i_n} y_{n,i_n+j_n}$ is stationary. ■

The theorem contains a rich set of testable implications for expectation formation. 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., $i_1 = i_2 = ... = i_n$) and over the same forecasting horizons (i.e., $j_1 = j_2 = ... = j_n$) are cointegrated. And forecasts of stock price consumption ratio, i.e., $(E_t \log P_{t+j} - E_t \log C_{t+j})$ is 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 $1960 - 1990$ (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.

The workhorse asset pricing models (e.g., Campbell and Cochrane (1999), Bansal, Kiku and Yaron (2012)) typically imply the existence of stationary price consumption ratios and/or price dividend ratios and assume that agents possess knowledge of the equilibrium pricing function, i.e., the equilibrium mapping from fundamentals to stock prices. Appendix B presents a long-run risk model, which clearly shows the stationarity of price-consumption (dividend) ratio from the analytical expressions. Appendix C reports that realized stock prices are cointegrated with realized fundamentals (aggregate consumption, dividend and output) using US data.

The knowledge of the equilibrium pricing function leads to the cointegration relation between stock price forecasts and fundamental forecasts. It is worthwhile to note that when investors have imperfect information about the behavior of fundamentals (like consumption) but understand stock prices are cointegrated with fundamentals, their forecast of stock prices and fundamentals are still cointegrated. In the following sections, we will show whether this cointegration relationship holds in survey forecasts.

3 Evidence from median and mean forecast data

This section describes the survey forecast data and presents the integration and cointegration properties of median (and mean) forecasts.

3.1 Data

Three sources of survey forecasts of US stock prices 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 2017. 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 first quarter of 2016. The survey collects business leaders' S&P 500 stock index forecasts over 4-quarter ahead. All survey forecasts of stock prices are deflated by 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.

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 B 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.[6] 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, following the literature, median (or mean) survey forecasts are interpreted as a proxy for the forecasts of the representative agent in models; see e.g., Eusepi and Preston (2011), Coibion and Gorodnichenko (2015), Piazzesi, Salomao and Schneider (2015), Kuang and Mitra (2016), and Adam, Marcet and Beutel (2017).[7] 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.[8] Later in Section 4, we present survey evidence using individual-level forecasts data (where forecasts of stock prices and fundamentals are from the same survey).

[6] Giglio, Maggiori, Stroebel and Utkus (2021) also provide evidence addressing these criticisms and strongly supports the use of survey expectations data in macro-finance models.

[7] With this view, the median (or mean) stock price forecasts from e.g., the Shiller Survey is a proxy for stock price expectations of the representative agent.

[8] 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, Marcet and Beutel (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.

3.2 Integration properties of the forecasts

Table 2: **Integration properties of median stock price forecasts**

P values			
Median	1Q ahead	2Q ahead	4Q ahead
Panel A: I(1) test			
Livingston stock price forecasts (1981Q4-2017Q4)			
Dickey–Fuller	*n.a*	0.530	0.554
Shiller stock price forecasts (1999Q1-2015Q2)			
Dickey–Fuller	0.692	0.752	0.712
CFO stock price forecasts (2001Q4-2016Q1)			
Dickey–Fuller	*n.a*	*n.a*	0.328
Panel B: I(2) test			
Livingston stock price forecasts (1981Q4-2017Q4)			
Dickey–Fuller	*n.a*	0.00	0.00
Shiller stock price forecasts (1999Q1-2015Q2)			
Dickey–Fuller	0.00	0.00	0.00
CFO stock price forecasts (2001Q4-2016Q1)			
Dickey–Fuller	*n.a*	*n.a*	0.00

Evidence 1A: Median stock price forecasts are I(1) but not I(2).

This section studies the integration properties of forecasts of the aggregate stock price index and aggregate fundamentals (aggregate consumption and dividend). Table 2 reports the p-values of Augmented Dickey-Fuller (ADF) test for median forecasts of stock prices. Panel A shows that for all surveys and all forecast horizons, DF-GLS test cannot reject the null hypothesis that median stock price forecasts are I(1) at the 10% significance level.[9] In addition, stock price forecasts are not I(2) processes as shown in Panel B. Similarly, for all forecasting horizons, Table 3 and 4 suggest that median consumption forecasts and dividend forecasts are I(1) but not I(2) processes, respectively.[10] Lemma 1 suggests that forecasts of stock prices, aggregate

[9] This result implies that this test cannot reject that stock price forecasts are I(1) at the 5% or 1% significance level either.

[10] Table A.3 and A.4 suggest similar results for mean forecasts of stock prices and consumption.

consumption and dividend from typical full-information RE stock pricing models (e.g., the long-run risks model) are I(1) but not I(2) processes, consistent with the evidence here.

Table 3: **Integration properties of median SPF consumption forecasts over different periods**

P values			
Median	1Q ahead	2Q ahead	4Q ahead
Panel A: SPF consumption forecasts - I(1) test			
Period: 1981Q4-2017Q4			
Dickey–Fuller	0.860	0.859	0.875
Period: 1999Q1-2015Q2			
Dickey–Fuller	0.112	0.125	0.116
Period: 2001Q4-2016Q1			
Dickey–Fuller	0.513	0.526	0.563
Panel B: SPF consumption forecasts - I(2) test			
Period: 1981Q4-2017Q4			
Dickey–Fuller	0.00	0.00	0.00
Period: 1999Q1-2015Q2			
Dickey–Fuller	0.00	0.00	0.00
Period: 2001Q4-2016Q1			
Dickey–Fuller	0.00	0.00	0.00

Evidence 1B: Median aggregate consumption forecasts are I(1) but not I(2).

Table 4: **Integration properties of median (and mean) forecasts of dividend**

P values		
1-year ahead	Median forecasts	Mean forecasts
Panel A: I(1) test		
IBES dividend forecasts (2003Q1-2015Q3)		
Dickey–Fuller	0.950	0.949
Panel B: I(2) test		
IBES dividend forecasts (2003Q1-2015Q3)		
Dickey–Fuller	0.00	0.00

Evidence 1C: Median (and mean) aggregate dividend forecasts are I(1) but not I(2).

3.3 No cointegration with imposing theoretical restrictions

Recall Theorem 3 implies that in typical full-information RE asset pricing models, stock price forecasts and consumption (or dividend) forecasts made at the same dates or over possibly different horizons are cointegrated with cointegrating vector (1, -1). 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 5 reports the test results of 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 1-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 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.[11] The same conclusion is reached with mean forecasts, see Table A.5 in Appendix D.

Table 6 reports the test results of whether median (and mean) forecasts of aggregate dividend are cointegrated with the forecasts of stock prices. All tests, including PP test, DF-GLS test, and KPSS tests, indicate that stock price forecasts are not cointegrated with dividend forecasts with cointegrating vector (1, -1).

Table 5: **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)	$n.a$	-2.210	-2.166	-2.155
10% critical value	$n.a$	-2.591	-2.591	-2.591
DF-GLS	$n.a$	-0.170	-0.363	-0.369
10% critical value	$n.a$	-1.842	-1.825	-1.825
KPSS	$n.a$	0.500	0.240	0.240
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)	-2.441	-2.450	-2.451	-2.459
10% critical value	-2.597	-2.597	-2.597	-2.597
DF-GLS	-0.919	-0.915	-0.917	-0.919
10% critical value	-1.929	-1.929	-1.929	-1.929
KPSS	0.439	0.438	0.437	0.436
5% critical value	0.146	0.146	0.146	0.146

Evidence 2: Median stock price forecasts and consumption forecasts are not cointegrated with the vector $(1, -1)$.

[11] 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 6: **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
5% critical value	-3.189	-3.189
KPSS	0.272	0.271
5% critical value	0.146	0.146

Evidence 3: Median (and mean) dividend forecasts and stock price forecasts are not cointegrated.

3.4 No cointegration without imposing theoretical restrictions

This section tests cointegration 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, Table 7 reports the results of testing the cointegration between stock price forecasts and consumption forecasts over the same or different horizons.[12] Again, the last column of Panel A and B are the testing results of using 4-quarter-ahead stock price forecasts and 1-quarter-ahead consumption forecasts. Table 8 reports the results for testing the cointegration between stock price forecasts and dividend forecasts.

The test results uniformly suggest that we cannot reject the null hypothesis that stock price forecasts are not cointegrated with consumption (or dividend) forecasts at the 10% significance level and over the same or different forecasting horizons, as all test statistics are greater than the corresponding 10% critical values. The test results are robust to using mean forecasts, see Table A.6 in Appendix D.

[12] We report the Engle–Granger test results without incorporating the trend component. Our test results are robust when the trend is included. The Engel-Granger test's critical values have been calculated by MacKinnon (1996).

Table 7: **No cointegration test between median stock price forecasts and consumption forecasts (without imposing any vector)**

Engle–Granger test				
Panel A: *Livingston stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q P &1Q C
Test stats.	*n.a*	-1.566	-1.539	-1.563
10% critical value	*n.a*	-4.022	-4.022	-4.022
Panel B: *Shiller stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q P &1Q C
Test stats.	-3.317	-3.337	-3.144	-3.233
10% critical value	-4.038	-4.038	-4.038	-4.038
Panel C: *CFO stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	3Q ahead	4Q ahead
Test stats.	-2.559	-2.682	-2.828	-2.939
10% critical value	-4.062	-4.062	-4.062	-4.062

Evidence 4: Median stock price forecasts are not cointegrated with consumption forecasts without imposing any cointegrating vector.

Table 8: **No cointegration between stock price forecasts and dividend forecasts (without imposing any vector)**

Engle–Granger test		
	Median forecasts	Mean forecasts
Engle-Granger test	-1.038	-1.051
10% critical value	-3.130	-3.130

Evidence 5: Median (and mean) stock price forecasts and dividend forecasts are not cointegrated without imposing any cointegrating vector.

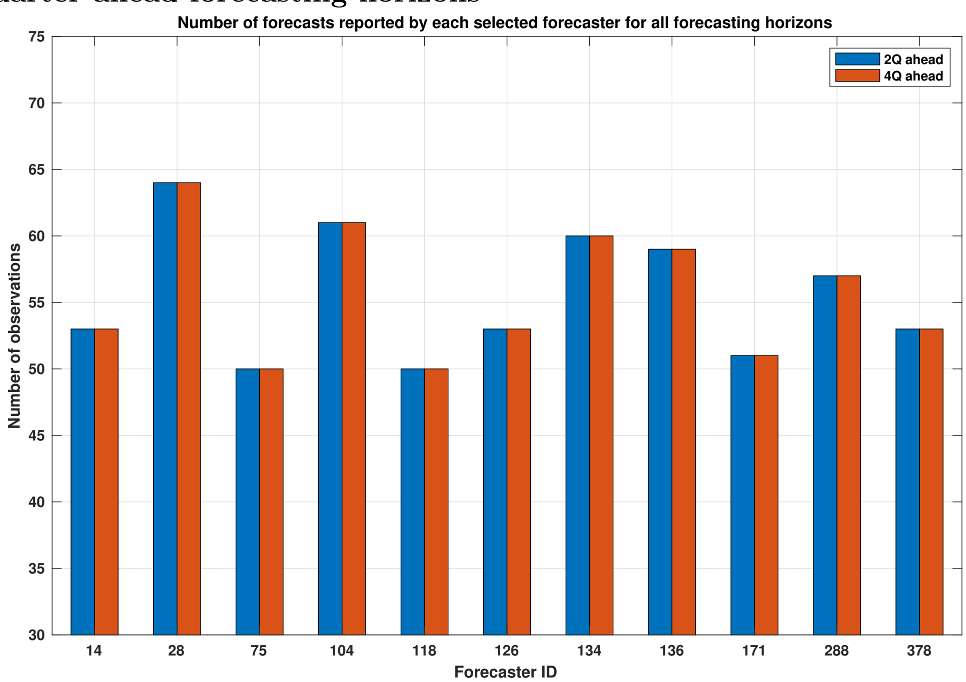
4 Evidence from individual forecasts

This section presents new survey evidence using individual-level forecasts data.

4.1 Data

The Livingston survey provides stock price forecasts and output forecasts of individual forecasters. Two forecasting horizons are available: 2-quarter and 4-quarter ahead. This allows us to test the cointegration between stock price forecasts and output forecasts at the individual level.[13] Stock prices and output typically share a common trend which are driven by a unit-root productivity process and cointegrate with each other as in production-based asset-pricing models (Jermann, 1998; Boldrin, Christiano and Fisher, 2001). To test whether stock price forecasts are cointegrated with output forecasts at the individual level, we select individuals whose observations are larger than 50. Figure 1 plots individual forecasters' ID and the number of observations for each ID. Real stock price forecasts are constructed by deflating survey stock price forecasts using the same individual's inflation forecasts. Survey output forecasts are rebased in the same way as consumption forecasts; the latter is explained in Appendix A.

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

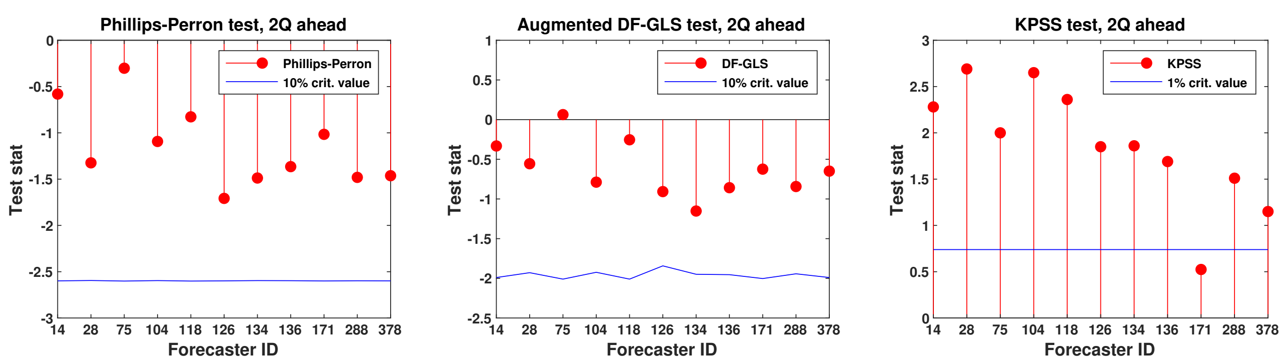


[13]The Livingston survey asks respondents their forecasts of aggregate output and does not ask forecasts of consumption or dividend.

4.2 No cointegration between stock price forecasts and aggregate output forecasts made over the same horizon

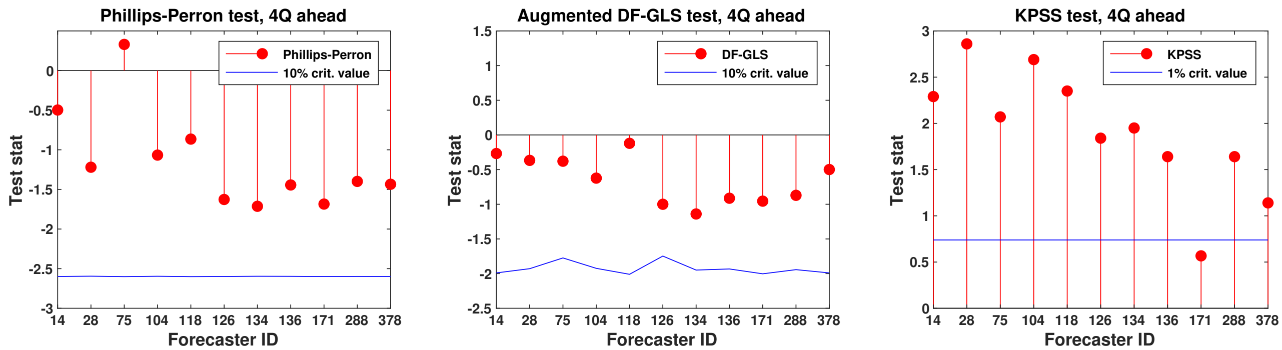
We firstly test cointegration relationship between individual output forecasts and stock price forecasts over the same horizon with imposing the theory-implied $(1, -1)$ cointegrating vector.[14] Figure 2 and 3 visualize test statistics against the corresponding critical values from PP, DF-GLS, and KPSS tests, using forecasts of 11 forecasters over 2-quarter ahead and 4-quarter ahead, respectively. The test statistics are pinned down by the circle at the end of each red stem, while the corresponding critical value locates on the blue lines. Forecaster's IDs are shown on the x-axis. For all forecasters, the test statistics of PP and DF-GLS tests stay above the critical values in all cases. For KPSS tests, the test statistics for all forecasters are above the corresponding critical values (except for the forecaster with the ID number 171). Those results generally suggest no cointegration between stock price forecasts and output forecasts at the individual level.

Figure 2: Cointegration tests between 2Q-ahead individual-level forecasts of output and stock prices



[14] 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.

Figure 3: Cointegration tests between 4Q-ahead individual-level forecasts of stock prices and output



Evidence 6A: Individual stock price forecasts and output forecasts over the same horizon are not cointegrated with the vector (1, -1).

4.3 No cointegration between stock price forecasts and aggregate output forecasts made over different horizons

This section tests cointegration between individual-level forecasts of output and stock prices over different forecasting horizons and with imposing the theory-implied $(1, -1)$ cointegrating vector. Figure 4 (or 5) reports the test results produced 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 output forecasts for 11 forecasters. Similar to the results in Section 4.2, the test statistics of PP and DF-GLS tests for all forecasters stay above the critical values in all cases. For KPSS tests, the test statistics for all forecasters are above the corresponding critical values (except for the forecasters with the ID number 171 and 378). These results suggest that for almost all forecasters, there is no cointegration between stock price forecasts and output forecasts made over different horizons.

Figure 4: Cointegration tests between individual-level 2Q-ahead stock price forecasts and 4Q-ahead output forecasts

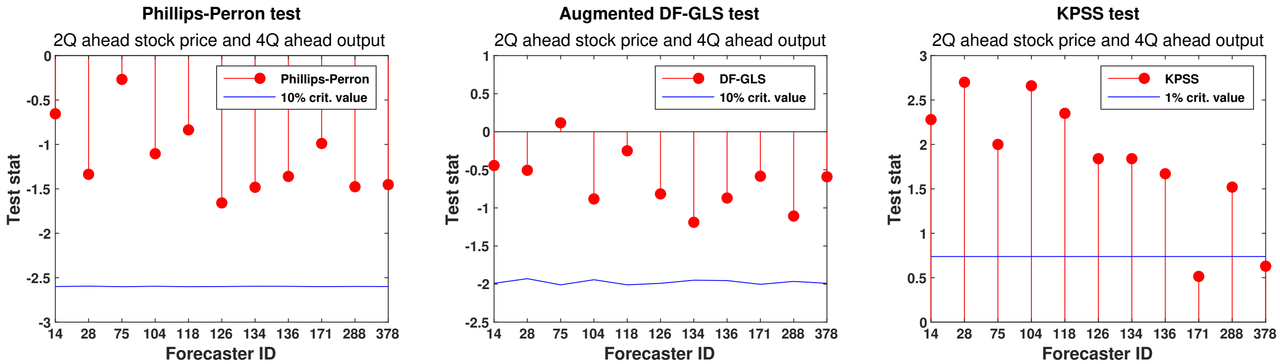
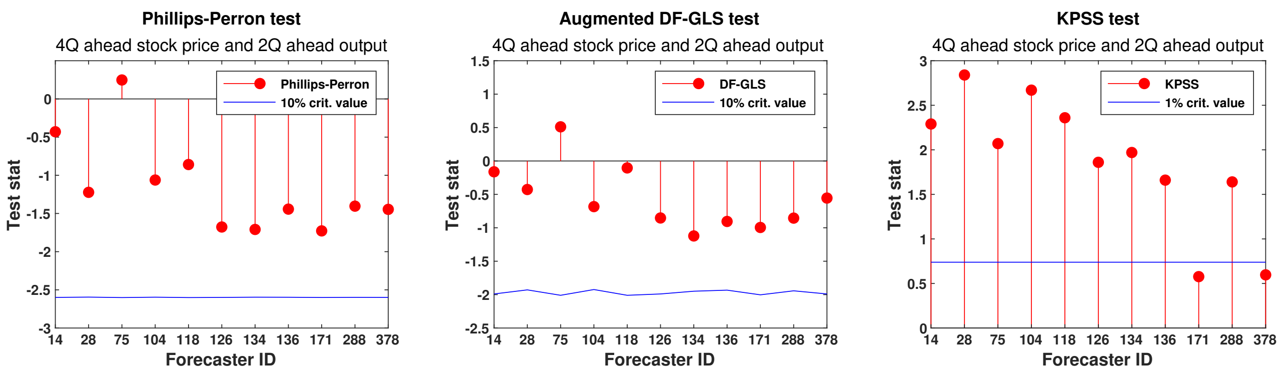


Figure 5: Cointegration tests between individual-level 4Q-ahead stock price forecasts and 2Q-ahead output forecasts



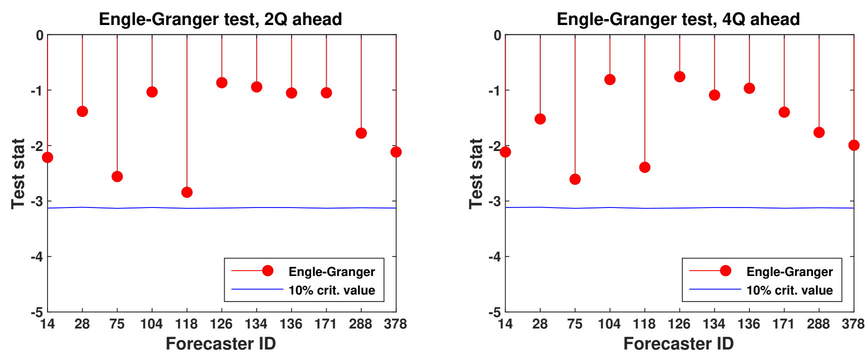
Evidence 6B: Individual stock price forecasts and output forecasts over different horizons are not cointegrated with the vector (1, -1).

4.4 Individual-level cointegration tests without imposing theoretical restrictions

This section tests cointegration between individual-level stock price forecasts and output forecasts without imposing any cointegrating vector. Figure 6 reports the testing results produced by EG test, using 2-quarter (or 4-quarter) ahead stock price forecasts and output forecasts for 11 forecasters made over the same forecasting horizon. Figure 7 reports the same results using forecasts made over different forecasting horizons. The test statistics of EG tests stay above the critical values in all cases. This suggests no cointegration between stock price forecasts and output forecasts for any cointegrating vector.

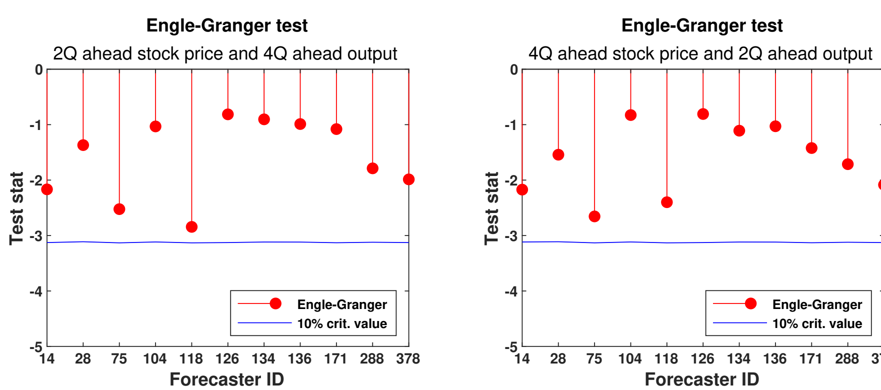
The forecasters in Livingston survey are experts from various sectors. According to their IDs in Figure 1, these sectors include academic institutions, commercial banking, investment banking and nonfinancing business. Overall, our results imply that almost all professional forecasters, regardless of their sectors, do not utilize the cointegration relation between stock prices and output implied in standard asset pricing models to forecast.

Figure 6: Cointegration tests between individual-level forecasts of output and stock prices, made over the same horizon



Evidence 7A: Individual stock price forecasts and output forecasts over the same horizon are not cointegrated without imposing any cointegrating vector.

Figure 7: Cointegration tests between individual-level forecasts of stock prices and output, made over different horizons



Evidence 7B: Individual stock price forecasts and output forecasts over different horizons are not cointegrated without imposing any cointegrating vector.

5 Econometric issues and discussions

This section considers and addresses several issues of econometric testing.

5.1 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 (Krämer and Ploberger, 1992; Brown, Durbin, and Evans, 1975) and the Gregory and Hansen (1996) cointegration test.

The Recursive Cusum test investigates parameter stability with the null hypothesis being no structural break. The test statistics are based on whether the time series abruptly changes in a way not predicted by the model across rolling samples. Table 9 displays the Recursive Cusum test statistics and the corresponding 5% critical value, assuming OLS residuals for forecasts of stock price-consumption ratios. The test statistics are all below the corresponding critical values. This implies that the Recursive Cusum tests indicate that no structural break is found in the estimated coefficients from the augmented DF regression. Similar results are obtained with recursive residuals and are not reported here for brevity.

For robustness, we also employ Gregory-Hansen test for testing potential structural breaks. The null hypothesis of this test assumes the existence 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 10 reports the Gregory–Hansen test statistics and the corresponding critical values. The null hypothesis is not rejected for all combinations of stock price forecasts and consumption forecasts. This implies that there is no cointegration between the two forecasts, taking into account a structural break.

Table 11 reports the results of structural break tests for median and mean forecasts of stock price-dividend ratios. The Recursive Cusum test in Panel A shows that there exists no structural break in the estimated coefficients. In addition, the test results of the Gregory–Hansen test imply no cointegration between stock price forecasts and dividend forecasts assuming the existence of a structural break.

Similarly, as shown in Figure 8 and 9, the results are robust once we consider structural breaks on the individual forecasts. The Recursive Cumsum tests suggest that all individual forecasts data reject the existence of a structural break. Moreover, the Gregory-Hansen test suggests that there is no cointegration between stock price forecasts and output forecasts for almost all individuals, taking into account a structural break.

Table 9: **Test for structural break in median forecasts of stock price-consumption ratios**

Cusum test (OLS residual)				
Panel A: *Livingston stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q Y &1Q C
Test stats.	*n.a*	0.721	0.790	0.786
5% critical value	*n.a*	1.358	1.358	1.358
Panel B: *Shiller stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q Y &1Q C
Test stats.	1.037	1.044	0.978	0.988
5% critical value	1.358	1.358	1.358	1.358
Panel C: *CFO stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	3Q ahead	4Q ahead
Test stats.	1.278	1.274	1.270	1.268
5% critical value	1.358	1.358	1.358	1.358

Evidence 8A: No structural break is detected in median forecasts of stock price-consumption ratio.

Table 10: **Gregory-Hansen cointegration tests between median stock price forecasts and consumption forecasts**

Gregory-Hansen cointegration test (assuming structural break)				
Panel A: *Livingston stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q P & 1Q C
Test stats.	*n.a*	-4.94	-5.05	-5.09
5% critical value	*n.a*	-5.50	-5.50	-5.50
Panel B: *Shiller stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q P & 1Q C
Test stats.	-3.52	-3.94	-3.64	-3.52
5% critical value	-5.50	-5.50	-5.50	-5.50
Panel C: *CFO stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	3Q ahead	4Q ahead
Test stats.	-5.02	-5.02	-4.99	-5.14
5% critical value	-5.50	-5.50	-5.50	-5.50

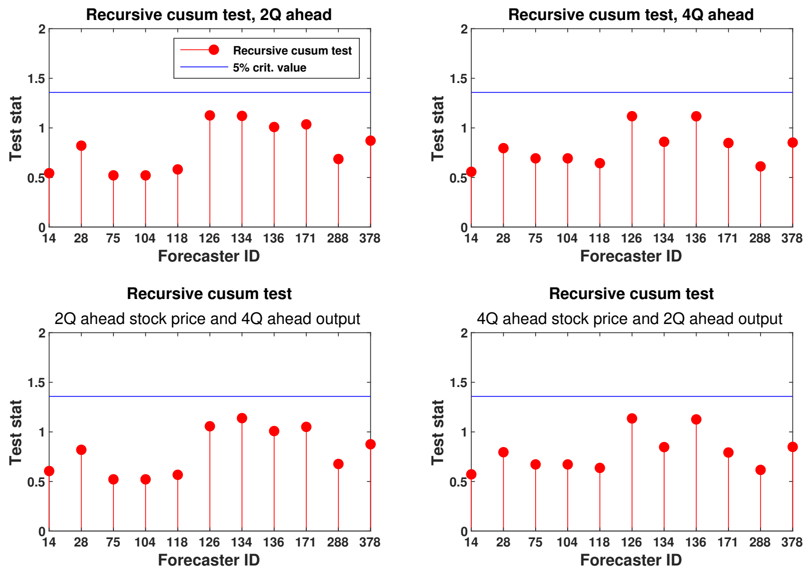
Evidence 8B: Median stock price forecasts are not cointegrated with consumption forecasts assuming the existence of a structural break.

Table 11: **Test for structural break in forecasts of stock price-dividend ratio**

Addressing issues related to structural break		
Panel A: *Cusum test (OLS residual) for structural break*		
	Median forecasts	Mean forecasts
Test stats.	0.557	0.539
5% critical value	1.224	1.224
Panel B: *Gregory-Hansen cointegration test*		
	1Q ahead	2Q ahead
Test stats.	-5.21	-5.24
5% critical value	-5.50	-5.50

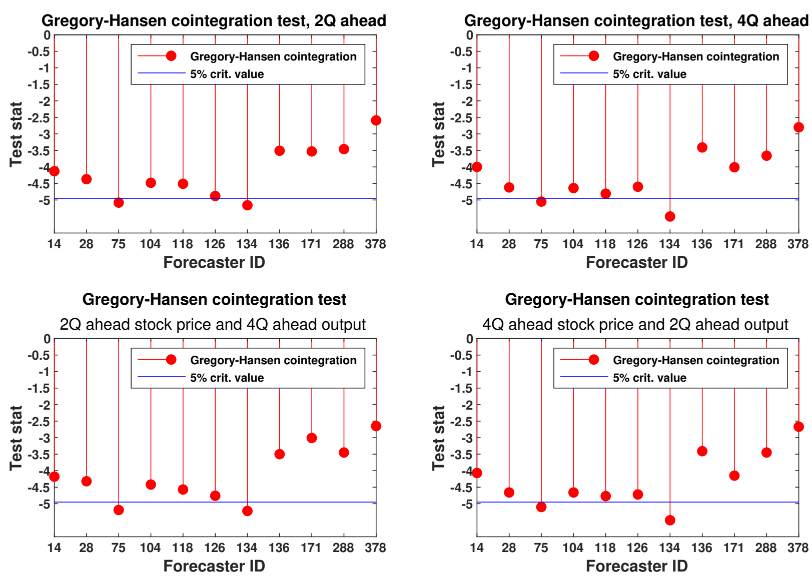
Evidence 9A: No structural break is detected in median (or mean) forecasts of stock price-dividend ratio.
Evidence 9B: Median (or mean) forecasts of stock price are not cointegrated with forecasts of dividend assuming the existence of a structural break.

Figure 8: **Illustration of individual level recursive Cusum test for structural break**



Evidence 10A: No structure break is detected in individual-level forecasts of stock price-output ratios.

Figure 9: **Illustration of individual-level Gregory-Hansen cointegration test**

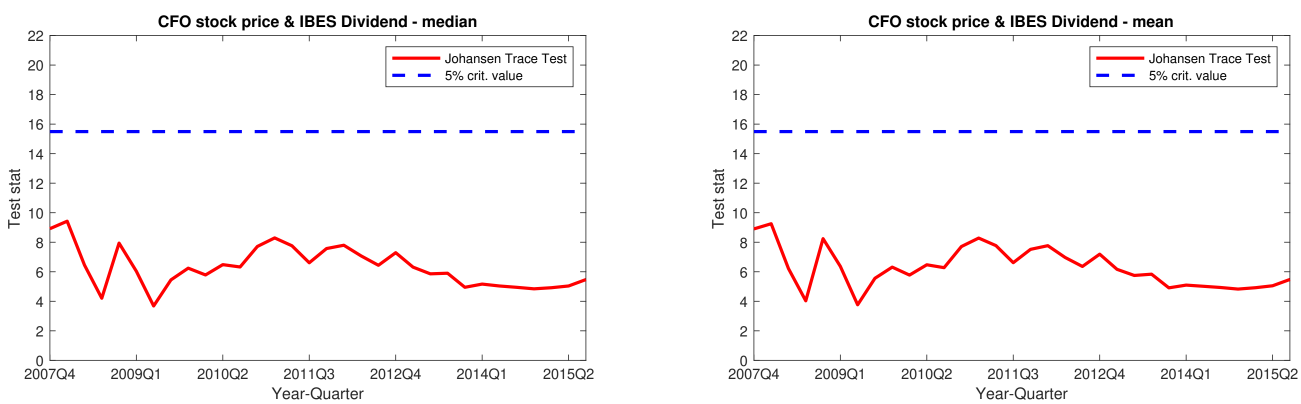


Evidence 10B: For almost all forecasters, individual-level forecasts of stock prices are not cointegrated with forecasts of output assuming the existence of structure break.

5.2 Sample size

The paper uses some of the most powerful tests like the DF-GLS tests.[15] We also 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 Johansen (1991) trace tests. Figure 10 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.1 - A.6 plot the test statistics (red 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.[16]

Figure 10: Recursive Johansen trace test (rank = 0) for median and mean forecasts of stock prices (CFO) and dividend (IBES)



Evidence 11: Forecasts of CFO stock prices are not cointegrated with IBES forecasts of dividends. Appendix E shows evidence from recusive Johansen trace tests for median (and mean) stock price forecasts and consumption forecasts.

[15]The power of the standard Dickey-Fuller class of unit root tests was frequently criticized in the 1980s and 1990s, 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.

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

Second, theorem 3 implies 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 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 12, we test cointegration between Livingston median stock price forecasts with i_1 = 57H1, 57H2, ..., 17H2 and SPF median consumption forecasts with i_2 = 84Q1, 84Q2, 84Q3, ..., 14Q2.[17] Similarly, we test cointegration when i_1 = 57H1, 57H2, ..., 17H2 and i_2 = 87Q4, 88Q1, ..., 18Q1 in Panel B and when i_1 =59H1, 59H2, ..., 17H2 and i_2 = 88Q4, 89Q1, ..., 18Q1 in Panel C. 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 Appendix B, 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-quarter- 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 13 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.

[17] "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.

Table 12: No cointegration between $E_{i_1} \log P_{i_1+j_1}$ & $E_{i_2} \log C_{i_2+j_2} : i_1 \neq i_2$

Panel A: i_1 = 57H1, 57H2, ..., 17H2; i_2 = 84Q1, 84Q2, ..., 14Q2				
I(1) test	$j_1 = j_2 = 2$	$j_1 = j_2 = 4$	j_1= 2, j_2 = 4	j_1= 4, j_2= 2
PP (Z_t statistics)	−1.064	−0.948	−1.069	−0.943
10% critical value	−2.579	−2.579	−2.579	−2.579
DF-GLS	−0.844	−0.727	−0.843	−0.728
10% critical value	−1.786	−1.786	−1.786	−1.786
KPSS test	1.90	1.97	1.89	1.98
1% critical value	0.739	0.739	0.739	0.739
Panel B: i_1 = 57H1, 57H2, ..., 17H2; i_2 = 87Q4, 88Q1, ..., 18Q1				
I(1) test	$j_1 = j_2 = 2$	$j_1 = j_2 = 4$	j_1= 2, j_2 = 4	j_1= 4, j_2= 2
PP (Z_t statistics)	−1.008	−0.901	−1.007	−0.901
10% critical value	−2.579	−2.579	−2.579	−2.579
DF-GLS	−0.876	−0.770	−0.880	−0.766
10% critical value	−1.786	−1.786	−1.786	−1.786
KPSS test	1.84	1.90	1.83	1.91
1% critical value	0.739	0.739	0.739	0.739
Panel C: i_1 = 59H1, 59H2, ..., 17H2; i_2 = 88Q4, 89Q1, ..., 18Q1				
	$j_1 = j_2 = 2$	$j_1 = j_2 = 4$	j_1= 2, j_2 = 4	j_1= 4, j_2= 2
PP (Z_t stat.)	−0.963	−0.861	−0.964	−0.860
10% critical value	−2.579	−2.579	−2.579	−2.579
DF-GLS	−0.980	−0.892	−0.979	−0.893
10% critical value	−1.792	−1.792	−1.792	−1.792
KPSS test	1.85	1.92	1.85	1.92
1% critical value	0.739	0.739	0.739	0.739

Note: cointegration tests utilize 122 pairs of observations in panel A and B and 118 pairs of observations in panel C.

Evidence 12: Median stock price forecasts and consumption forecasts made at different dates are not cointegrated with the vector (1,-1).

Table 13: No cointegration between median and mean forecasts of P and C

KPSS test	2Q ahead	4Q ahead
Panel A: median Livingston forecasts		
Test statistic	0.500	0.240
5% critical value	0.146	0.146
5% critical value (corrected)	0.185	0.185
Panel B: mean Livingston forecasts		
Test statistic	0.512	0.242
5% critical value	0.146	0.146
5% critical value (corrected)	0.185	0.185

Evidence 13: Median/mean forecasts of stock price are not cointegrated with forecasts of consumption from the Monte Carlo study.

5.3 Multiple testing problem

Section 4 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 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 14 reports corrected PP testing outcomes for both forecasts of stock price-output ratios for 11 forecasters, using FDR sharpened q-values. It shows no existence of cointegration between forecasts of stock price and output, even after considering the multiple testing problem.

Table 14: **Individual-level cointegration testing adjusted for multiple testing problem**

PP tests	**Using FDR sharpened q-values**	
Forecasts of stock prices and output	**No. of no cointegration**	**Proportion of no cointegration**
2Q ahead	11	100%
4Q ahead	11	100%
2Q ahead & 4Q ahead	11	100%
4Q ahead & 2Q ahead	11	100%

Evidence 14: Individual-level forecasts of stock price are not cointegrated with output forecasts, after adjusted for 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 15 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.

Table 15: **Test results of Pesaran panel cross-sectional dependence test**

Number of panels: 11 in each test				
H_0: forecasts are cross-sectionally independent. H_1: forecasts are cross-sectionally dependent.				
	2Q ahead	4Q ahead	2Q & 4Q ahead	4Q & 2Q ahead
Forecasts of stock price-output ratio				
P-values	0.000	0.000	0.000	0.000
Average correlation coeff.	0.84	0.91	0.83	0.86

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 (2003). 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.[18] Table 16 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.

Table 16: **P-values of Pesaran panel cointegration test with the cointegrating vector** $(1, -1)$

CADF panel unit root test	**Number of panels**: 11 in each test			
H_0: All panels are non-stationary; H_1: At least one panel is stationary				
	1Q ahead	2Q ahead	3Q ahead	4Q ahead
P-values	0.510	0.288	0.412	0.367

Evidence 15: The CADF panel cointegration tests suggest that individual forecasters' forecasts of stock prices are not cointegrated with forecasts of output.

6 Conclusion

This paper demonstrates that macroeconomic and financial models typically impose a large number of cointegration relationships between forecasts of endogenous variables and exogenous variables (or among forecasts of endogenous variables). For instance, standard asset-pricing models typically impose a large number of cointegration restrictions between forecasts of stocks prices and forecasts of fundamentals. Employing several widely used datasets on survey expectations, the paper shows that survey stock price forecasts are not cointegrated with forecasts of fundamentals (aggregate consumption, dividend, and output) at both median (or mean) and

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

individual level. The results are robust to a large number of considerations, such as using different tests, forecasts over different horizons, and forecasts made at the same or different dates, with or without imposing the theory-implied cointegrating vector, and considering the multiple testing problem, small sample problem and structural breaks.

The new survey findings have potential implications for modeling expectation formation in stock markets. Standard asset pricing models typically imply that agents possess knowledge of the equilibrium pricing function, i.e., the equilibrium mapping from realization (or forecasts) of fundamentals to stock prices.[19] This knowledge leads to the cointegration relation between stock price forecasts and fundamental forecasts in these models. To reconcile the survey evidence, it appears natural to relax agents' knowledge of the equilibrium pricing function, as is present in, e.g, adaptive learning models.[20] In this type of learning models, investors have imperfect knowledge of stock markets and form subjective stock price expectations which could be delinked from fundamental forecasts. We leave for future work to reconcile the survey findings with a structural model. As the quality of survey expectation data continue improving, applying unit root econometrics to expectation data – as is done in the paper – may be a promising avenue to provide useful guidance on the modeling of expectation formation.

References

Adam, Klaus, Pei Kuang, and Albert Marcet (2012): "House Price Booms and the Current Account", NBER Macroeconomics Annual, volume 26, 2012, p. 77 - 122.

Adam, Klaus, Albert Marcet, and Johannes Beutel (2017): "Stock Price Booms and Expected Capital Gains", American Economic Review, vol 107(8), 2352-2408.

Adam, Klaus, and Stefan Nagel (2022): "Expectations Data in Asset Pricing", National Bureau of Economic Research, Prepared for the Handbook of Economic Expectations.

[19]These include full information rational expectations (RE) 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, Johannes and Lochstoer, 2016), consumption sentiment (Jin and Sui, 2018), and "agree to disagree" heterogeneous beliefs models (Ehling et al., 2018).

[20]Examples include Carceles-Poveda and Giannitsarou (2008), Lansing (2010, 2019), Kuang (2014), Branch and Evans (2010, 2011), Boswijk et al. (2007), and Adam et al. (2017).

Anderson, M. (2008): ”Multiple Inference and Gender Differences in the Effects of Early Entervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects”, Journal of the American Statistical Association, 2008, vol 103 (484), 1481–1495.

Andre, Peter, Carlo Pizzinelli, Christopher Roth, and Johannes Wohlfart (2022): ”Subjective Models of the Macroeconomy: Evidence From Experts and Representative Samples”, Review of Economic Studies, forthcoming.

Bansal, Ravi, Dana Kiku and Amir Yaron (2012): ”An Empirical Evaluation of the Long-Run Risk Model for Asset Prices”, Critical Finance Review, vol 1, 183-221.

Boldrin, Michele, Lawrence J. Christiano, and Jonas DM Fisher (2001): ”Habit Persistence, Asset Returns, and the Business Cycle”, American Economic Review, vol 91(1), 149-166.

Bordalo, P., Gennaioli, N., Ma, Y., & Shleifer, A. (2020): ”Overreaction in Macroeconomic Expectation”, American Economic Review, vol 110(9), 2748-82.

Boswijk, P., C. Homme, and S. Manzan (2007): ”Behavioral Heterogeneity in Stock Prices”, Journal of Economic Dynamics and Control, vol 31, 1938-1970.

Branch, W. and G. Evans (2010): ”Asset Return Dynamics and Learning”, Review of Financial Studies, vol 23(4), 1651-1680.

Branch, W. and G. Evans (2011): ”Learning about Risk and Return: A Simple Model of Bubbles and Crashes”, American Economic Journal: Macroeconomics, vol 3(3), 159-191.

Campbell, John and John Cochrane (1999): ”By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior”, Journal of Political Economy, vol 107, 205-251.

Carceles-Poveda, E and C. Giannitsarou (2008): ”Asset Pricing with Adaptive Learning”, Review of Economic Dynamics, vol 11(3), 629-651.

Carroll, C. (2003): ”Macroeconomic Expectations of Households and Professional Forecasters”, Quarterly Journal of Economics, vol 118, 269-298.

Cochrane, J.H., (1991): ”A Critique of the Application of Unit Root Tests”, Journal of Economic Dynamics and Control, vol 15, 274-285.

Coibion, Olivier and Yuriy Gorodnichenko (2015): ”Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts”, American Economic Review, vol 105 (8), 2644-2678.

Collin-Dufresne P., M. Johannes and L. Lochstoer (2016): ”Parameter Learning in General Equilibrium: The Asset Pricing Implications", American Economic Review, vol 106(3), 664-698.

Croce, Mariano Massimiliano (2014): "Long-run Productivity Risk: A New Hope for Production-based Asset Pricing?", Journal of Monetary Economics, vol 66, 13-31.

De La O, R. and S. Myers (2021): "Subjective Cash Flows and Discount Rates", Journal of Finance, vol 76 (3), 1339-1387.

Ehling, P., A. Graniero and C. Heyerdahl-Larsen (2018): "Asset Prices and Portfolio Choice with Learning from Experience", Review of Economic Studies, vol 85(3), 1752-1780.

Eusepi, S. and B. Preston (2011): "Expectations, Learning and Business Cycle Fluctuations", American Economic Review, vol 101(6), 2844-2872.

Evans, G.W. (1991): "Pitfalls in Testing for Explosive Bubbles in Asset Prices", American Economic Review, vol 81, 922-930.

Giglio S., M. Maggiori, J. Stroebel and S. Utkus (2021). "Five Facts about Beliefs and Portfolios", American Economic Review, vol 11(5), 1481-1522.

Golez, Benjamin, and Peter Koudijs (2018): "Four Centuries of Return Predictability", Journal of Financial Economics, vol 127(2), 248-263.

Greenwood, J Robin, and A Shleifer (2014): "Expectations of returns and expected returns", Review of Financial Studies, vol 27(3), 714-746.

Haldrup, N. and M. Jansson (2006): "Improving Size and Power in Unit Root Testing", in Palgrave Handbook of Econometrics, Volume 1: Econometric Theory, ed. by H. Hassani, T. C. Mills, and K. Paterson, Basingstoke, UK: Palgrave Macmillan, Chap. 7, 252-277.

Johansen, S. (1991):"Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models", Econometrica. vol 59 (6): 1551–1580.

Johansen, S. and A. R. Swensen (1999): "Testing Exact Rational Expectations in Cointegrated Vector Autoregressive Models", Journal of Econometrics, vol 93(1), 73-91.

Kuang, P. (2014). A Model of Housing and Credit Cycles with Imperfect Market Knowledge, European Economic Review, volume 70, 419–437.

Kuang, P. and K. Mitra (2016): "Long-run Growth Uncertainty", Journal of Monetary Economics, vol 79, 67-80.

Kuang, P., L. Tang, R. Zhang and T. Zhang (2022): "Forecast Disagreement about Long-run Macroeconomic Relationships", Journal of Economic Behavior & Organization, vol 200, p. 371 - 387.

Lansing, K. (2010): "Rational and Near-Rational Bubbles without Drift", Economic Journal, vol 120, 1149-1174.

Lansing, K. (2019): "Real Business Cycles, Animal Spiritis, and Stock Market Valuation", International Journal of Economic Theory, vol 15(1), 77-94.

Malmendier, U. and S. Nagel (2011): "Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?", Quarterly Journal of Economics, vol 126(1), 373-416.

Milani, F (2011): "Expectation Shocks and Learning as Drivers of the Business Cycle", Economic Journal, vol 121, 379-401.

Nagel, S. and Z. Xu (2018): "Asset Pricing with Fading Memory", University of Chicago mimeo.

Ng S. and P. Perron (2001): "Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power", Econometrica 69, no. 6, 1519-1554.

Phillips, Peter CB, and Pierre Perron (1988): "Testing for A Unit Root in Time Series Regression", Biometrika, vol 75(2), 335-346.

Appendix (Not for publication)

A Rebasing consumption forecasts data

Since the Survey of Professional Forecasters (SPF) began, there have been a number of changes of the base year in the national income and product accounts (NIPA). The forecasts for levels of consumption (SPF variable name: RCONSUM) use the base year that was in effect when the forecasters received the survey questionnaire. This Appendix explains how consumption forecasts data are rebased.

Table A.1 provides the base year in effect for NIPA variables (including consumption expenditures), reproduced from Table 4 of the documentation of the Survey of Professional Forecasters (p. 23). For rebasing, we use real consumption expenditures data of different vintages from the Real-Time Data Set for Macroeconomists managed by the Federal Reserve Bank of Philadelphia. The year 1996 is used as the common base year for all consumption forecast data. The data in each window needs to be rebased by multiplying a base ratio. For instance the 1959:Q4 real consumption in the window from 1996:Q1 to 1999:Q3 is 1409.5 while it is 1469.5 in 1999:Q4 to 2003:Q4 window and hence the ratio is 1469.5/1409.5.

Table A.1: Base years and ratios for rebasing

Range of Survey Dates	Base Year	Ratio
1976:Q1 to 1985:Q4	1972	3.31
1986:Q1 to 1991:Q4	1982	1.48
1992:Q1 to 1995:Q4	1987	1.23
1996:Q1 to 1999:Q3	1992	1.04
1999:Q4 to 2003:Q4	1996	1
2004:Q1 to 2009:Q2	2000	0.94
2009:Q3 to 2013:Q2	2005	0.84
2013:Q3 to present	2009	0.79

B Long-run Risks Model

Consider the long-run risks model studied in Bansal, Kiku and Yaron (2012). The representative agent with recursive preferences maximizes his life-time utility given by

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

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

$$\begin{aligned}
\Delta c_{t+1} &= \mu_c + x_t + \sigma_t \eta_{t+1}, \\
x_{t+1} &= \rho x_t + \varphi_e \sigma_t e_{t+1}, \\
\sigma_{t+1}^2 &= \overline{\sigma}^2 + \nu(\sigma_t^2 - \overline{\sigma}^2) + \sigma_w w_{t+1}, \\
\Delta d_{t+1} &= \mu_d + \phi x_t + \pi \sigma_t \eta_{t+1} + \varphi \sigma_t u_{d,t+1}.
\end{aligned}$$

$\mu_c + x_t$ 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 ratio

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

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

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.

C Cointegration between Realized Stock Prices and Fundamentals

This section tests for cointegration between realized stock prices and fundamentals with the cointegrating vector $(1, -1)$. Data on stock prices (S&P 500 index), aggregate consumption, dividend, and output for the US are downloaded from the website of Robert Shiller and the Federal Reserve Bank of St. Louis. The samples cover the same period as those of the survey forecast data. Table A.2 reports test results by applying the DF-GLS test to log stock prices to consumption (dividend or output) ratios. Panel A shows that the DF-GLS test rejects the null of unit root at the 10% level, in favor of cointegration between stock prices and consumption. Panel B (C) reports similar results for cointegration testing using stock prices and aggregate dividend (output), respectively.

Table A.2: **Tests of the cointegration with the vector $(1, -1)$ using realized data**

	Test stat.	**10% critical**
Panel A: *Realized (log) stock prices-consumption ratio*		
DF-GLS	-1.705*	-1.619
Panel B: *Realized (log) stock prices-dividend ratio*		
DF-GLS	-3.155*	-2.732
Panel C: *Realized (log) stock prices-output ratio*		
DF-GLS	-1.832*	-1.619

Note: *: the test statistics with one asterisk indicate that the corresponding test rejects the null of a unit root at the 10% significance level.
Sample period in Panel A and C is 1957Q1-2017Q2;
sample period in Panel B is 2003Q1 to 2015Q3.

D Evidence from mean forecasts

D.1 Integration properties of the forecasts

Table A.3: **Integration properties of mean stock price forecasts**

P values			
Median	1Q ahead	2Q ahead	4Q ahead
Panel A: I(1) test			
Livingston stock price forecasts (1981Q4-2017Q4)			
Dickey–Fuller	*n.a*	0.526	0.559
Shiller stock price forecasts (1999Q1-2015Q2)			
Dickey–Fuller	0.704	0.685	0.656
Panel B: I(2) test			
Livingston stock price forecasts (1981Q4-2017Q4)			
Dickey–Fuller	*n.a*	0.00	0.00
Shiller stock price forecasts (1999Q1-2015Q2)			
Dickey–Fuller	0.00	0.00	0.00

Evidence A.1: Mean stock price forecasts are I(1) but not I(2).

Table A.4: **Integration properties of mean SPF consumption forecasts over different periods**

P values			
Median	1Q ahead	2Q ahead	4Q ahead
Panel A: SPF consumption forecasts - I(1) test			
Period: 1981Q4-2017Q4			
Dickey–Fuller	0.852	0.850	0.875
Period: 1999Q1-2015Q2			
Dickey–Fuller	0.113	0.127	0.117
Period: 2001Q4-2016Q1			
Dickey–Fuller	0.516	0.509	0.509
Panel B: SPF consumption forecasts - I(2) test			
Period: 1981Q4-2017Q4			
Dickey–Fuller	0.00	0.00	0.00
Period: 1999Q1-2015Q2			
Dickey–Fuller	0.00	0.00	0.00
Period: 2001Q4-2016Q1			
Dickey–Fuller	0.00	0.00	0.00

Evidence A.2: Mean consumption and dividend forecasts are I(1) but not I(2).

D.2 No cointegration with imposing theoretical restrictions

Table A.5: **Cointegration tests between mean stock price forecasts and SPF 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)	$n.a$	-2.313	-2.142	-2.118
10% critical value	$n.a$	-2.591	-2.591	-2.591
DF-GLS	$n.a$	-0.241	-0.272	-0.293
10% critical value	$n.a$	-1.842	-1.825	-1.825
KPSS	$n.a$	0.512	0.242	0.242
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)	-2.050	-2.121	-2.157	-2.153
10% critical value	-2.594	-2.594	-2.594	-2.594
DF-GLS	-1.785	-1.794	-1.803	-1.815
10% critical value	-1.895	-1.895	-1.895	-1.895
KPSS	0.421	0.425	0.428	0.429
5% critical value	0.146	0.146	0.146	0.146
Panel C: *CFO stock priceforecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	3Q ahead	4Q ahead
PP (Z_t test)	-2.438	-2.452	-2.460	-2.465
10% critical value	-2.597	-2.597	-2.597	-2.597
DF-GLS	-0.924	-0.916	-0.915	-0.917
10% critical value	-1.929	-1.929	-1.929	-1.929
KPSS	0.439	0.438	0.437	0.436
5% critical value	0.146	0.146	0.146	0.146

Evidence A.3: Mean stock price forecasts and consumption forecasts are not cointegrated with the vector $(1, -1)$.

D.3 No cointegration without imposing theoretical restrictions

Table A.6: **Cointegration test for mean SPF forecasts without imposing the cointegrating vector** $(1, -1)$

Engle–Granger test				
Panel A: *Livingston stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q P &1Q C
Test stats.	*n.a*	-1.534	-1.523	-1.550
10% critical value	*n.a*	-4.022	-4.022	-4.022
Panel B: *Shiller stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q P &1Q C
Test stats.	-3.334	-3.283	-3.102	-3.140
10% critical value	-4.038	-4.038	-4.038	-4.038
Panel C: *CFO stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	3Q ahead	4Q ahead
Test stats.	-2.590	-2.794	-2.913	-3.024
10% critical value	-4.062	-4.062	-4.062	-4.062

Evidence A.4: Mean stock price forecasts are not cointegrated with consumption forecasts without imposing any cointegrating vector.

D.4 Structural breaks

Table A.7: **Test for structural break in mean forecasts of stock price-consumption ratios**

Test for structure break - Cusum test (OLS residual)				
Panel A: *Livingston stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q P &1Q C
Test stats.	*n.a*	0.615	0.761	0.760
5% critical value	*n.a*	1.358	1.358	1.358
Panel B: *Shiller stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q P &1Q C
Test stats.	1.059	1.019	0.991	1.001
5% critical value	1.358	1.358	1.358	1.358
Panel C: *CFO stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	3Q ahead	4Q ahead
Test stats.	1.278	1.276	1.274	1.271
5% critical value	1.358	1.358	1.358	1.358

Evidence A.5: No structural break is detected in mean forecasts of stock price-consumption ratios.

Table A.8: **Gregory-Hansen cointegration tests between mean stock price forecasts and SPF consumption forecasts**

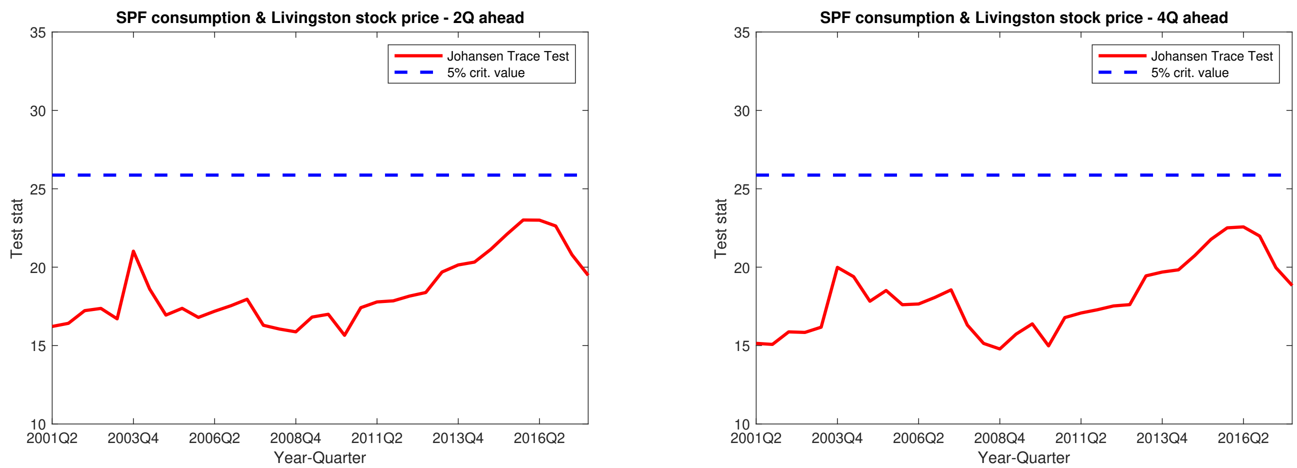
Gregory-Hansen cointegration test (assuming structural break)				
Panel A: *Livingston stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q Y & 1Q C
Test stats.	*n.a*	-4.96	-5.09	-5.11
5% critical value	*n.a*	-5.50	-5.50	-5.50
Panel B: *Shiller stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	4Q ahead	4Q Y & 1Q I
Test stats.	-3.51	-3.50	-3.56	-3.53
5% critical value	-5.50	-5.50	-5.50	-5.50
Panel C: *CFO stock price forecasts and SPF consumption forecasts*				
Median	1Q ahead	2Q ahead	3Q ahead	4Q ahead
Test stats.	-5.16	-5.14	-5.09	-5.05
5% critical value	-5.50	-5.50	-5.50	-5.50

Evidence A.6: Mean stock price forecasts are not cointegrated with consumption forecasts assuming the existence of a structural break.

E Recursive Johansen Trace testing results forecasts of stock prices and consumption

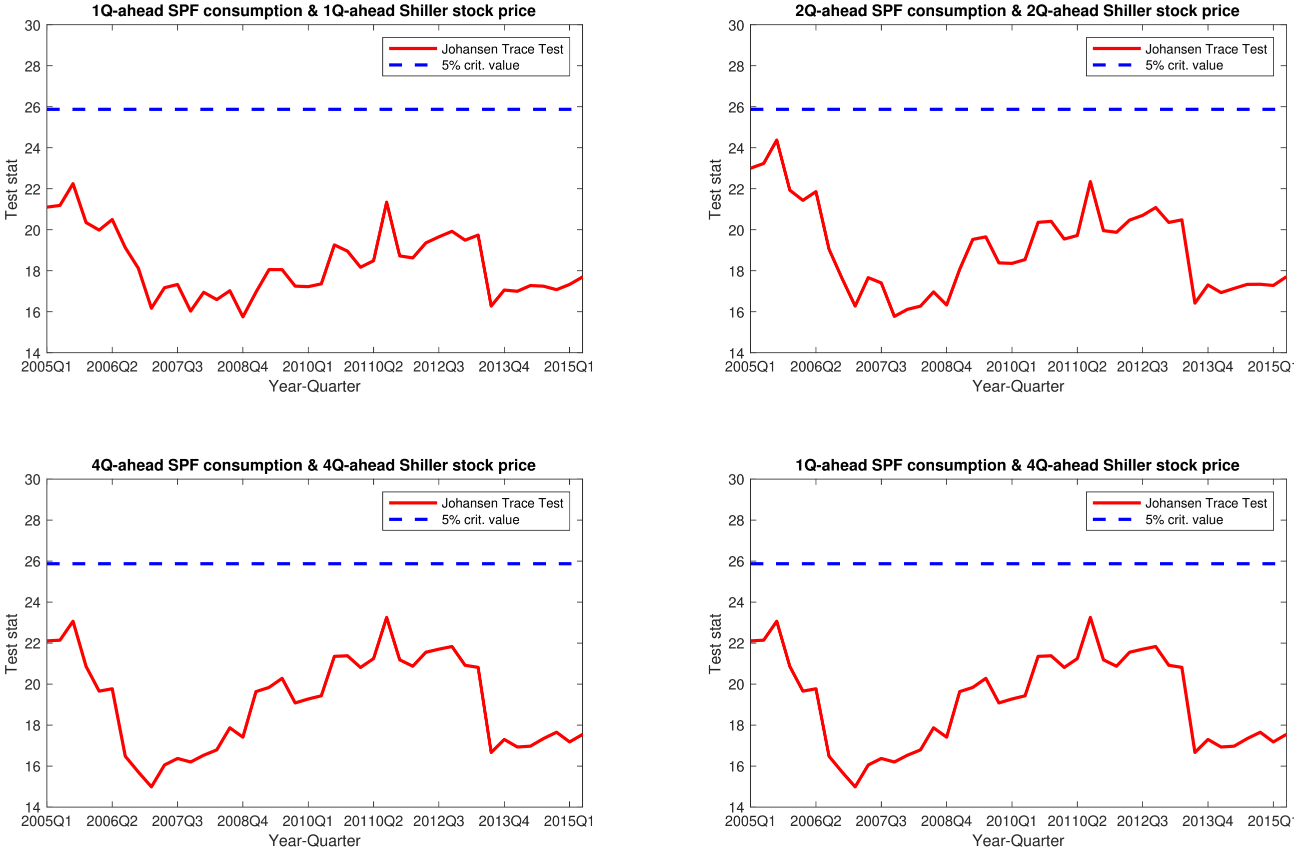
E.1 Recursive Johansen Trace testing for median forecasts

Figure A.1: Recursive Johansen trace test (rank = 0) for median forecasts of stock prices (Livingston) and consumption (SPF)



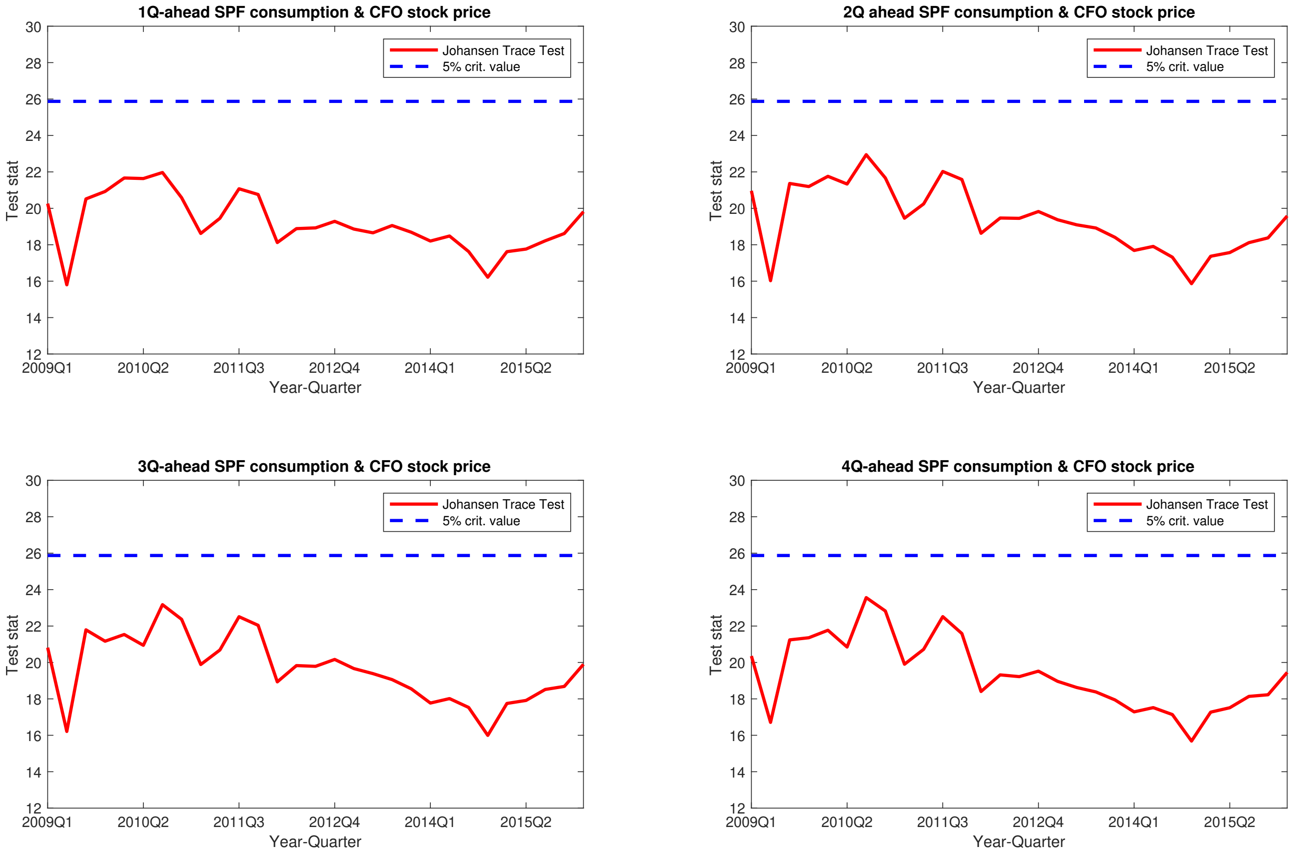
Evidence A.7: Median forecasts of Livingston stock prices are not cointegrated with median SPF consumption forecasts.

Figure A.2: Recursive Johansen trace test (rank = 0) for median forecasts of stock price (Shiller) and consumption (SPF)



Evidence A.8: Median forecasts of Shiller stock prices are not cointegrated with median SPF consumption forecasts.

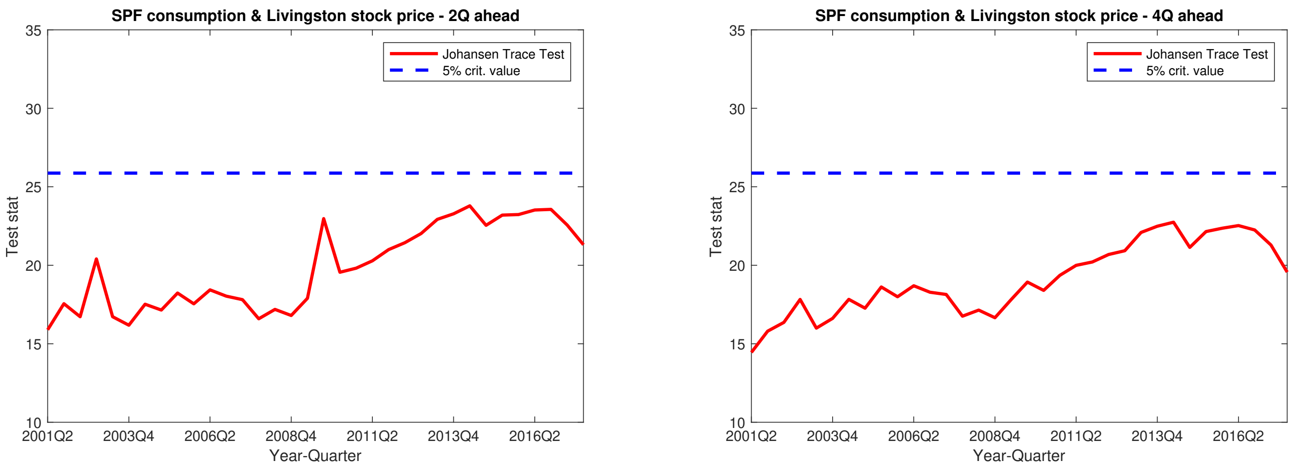
Figure A.3: Recursive Johansen trace test (rank = 0) for median forecasts of stock prices (CFO) and consumption (SPF)



Evidence A.9: Median forecasts of CFO stock prices are not cointegrated with median SPF consumption forecasts.

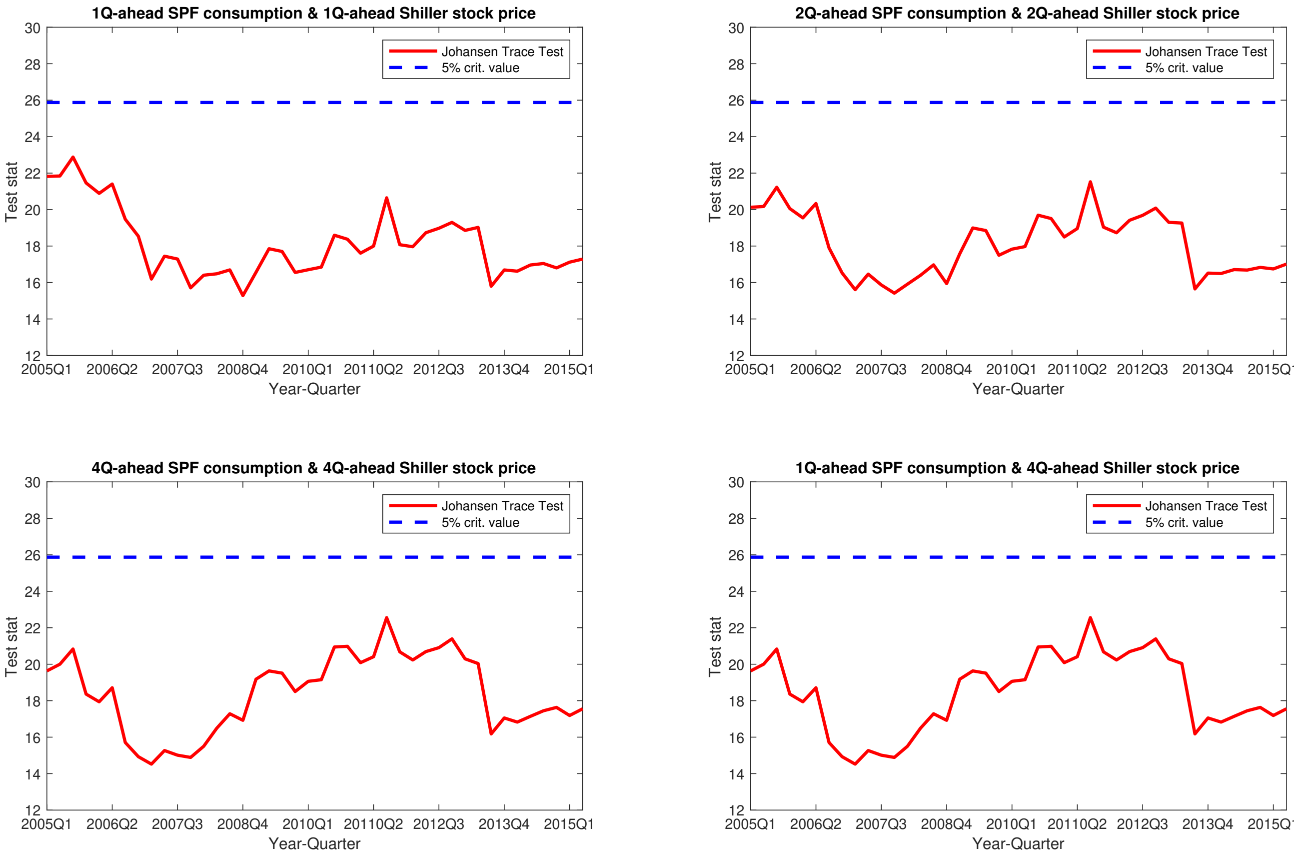
E.2 Recursive Johansen Trace testing for mean forecasts

Figure A.4: Recursive Johansen trace test (rank = 0) for mean Livingston stock price forecasts and SPF consumption forecasts



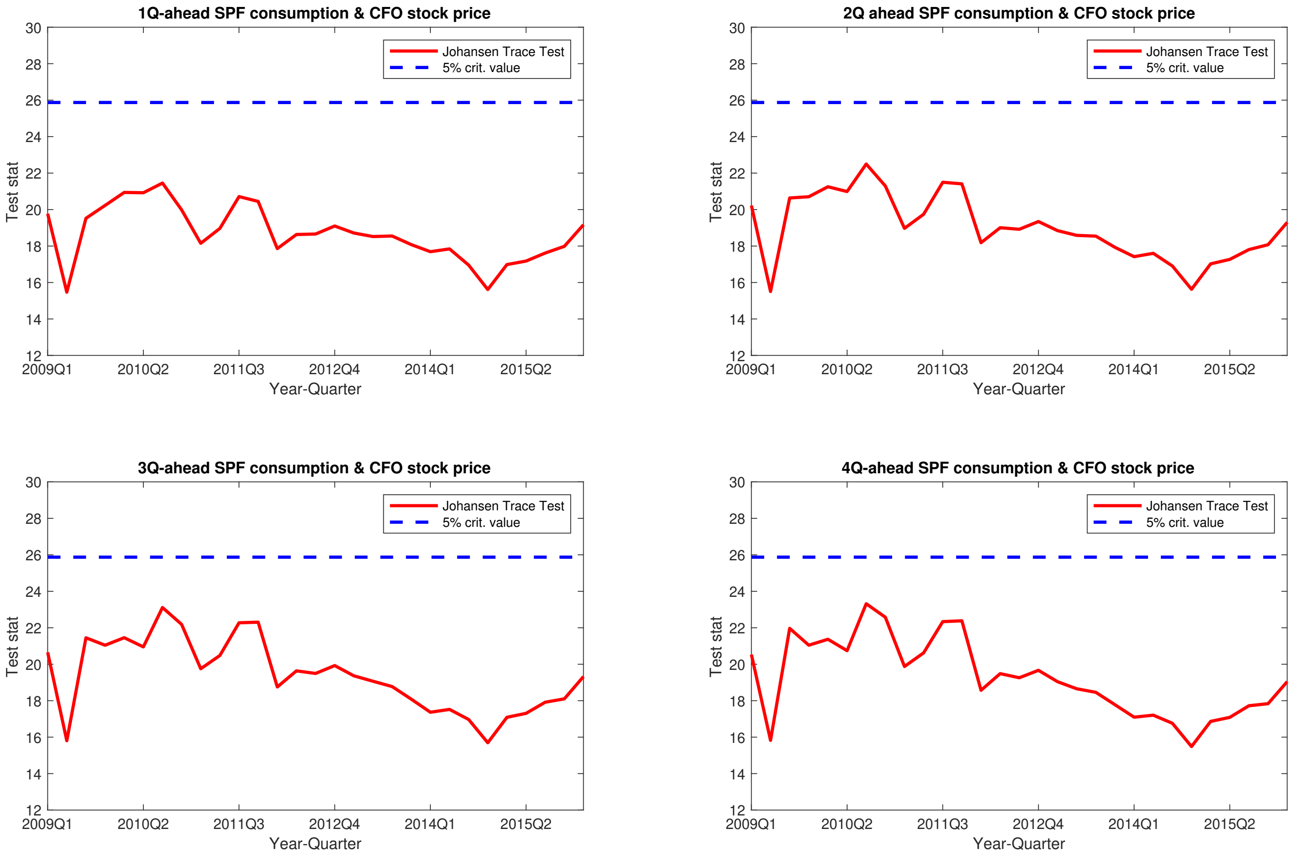
Evidence A.10: Mean forecasts of Livingston stock prices are not cointegrated with mean SPF consumption forecasts.

Figure A.5: Recursive Johansen trace test (rank = 0) for mean Shiller stock price forecasts and SPF consumption forecasts



Evidence A.11: Mean Shiller forecasts of stock prices are not cointegrated with mean SPF consumption forecasts.

Figure A.6: Recursive Johansen trace test (rank = 0) for mean CFO stock price forecasts and SPF consumption forecasts



Evidence A.12: Mean CFO forecasts of stock prices are not cointegrated with mean SPF consumption forecasts.

E.3 Recursive Johansen Trace testing for individual forecasts

Figure A.7: Recursive Johansen Trace test for individual-level forecasts (ID:126)

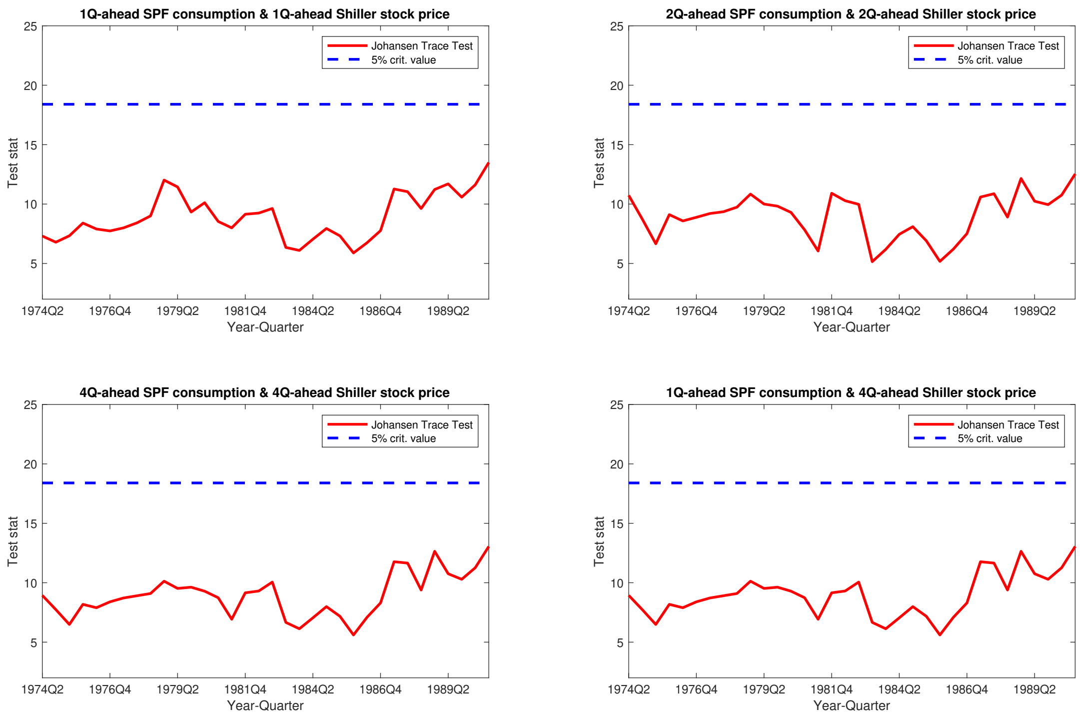


Figure A.8: Recursive Johansen Trace test for individual-level forecasts (ID:136)

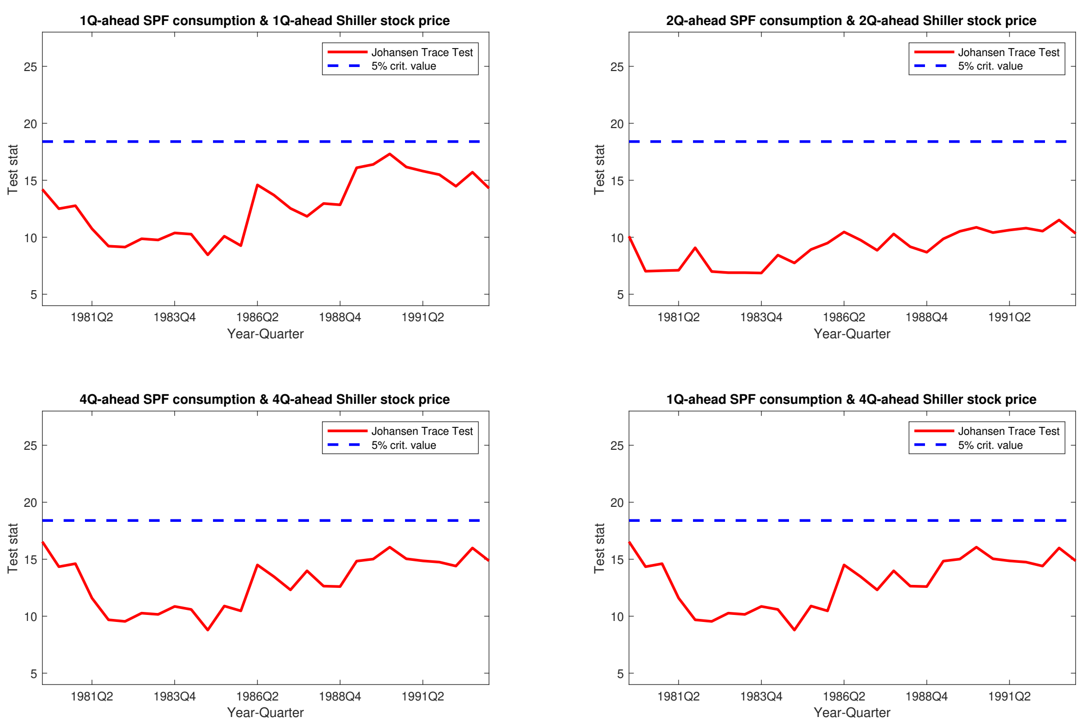


Figure A.9: Recursive Johansen Trace test for individual-level forecasts (ID:288)

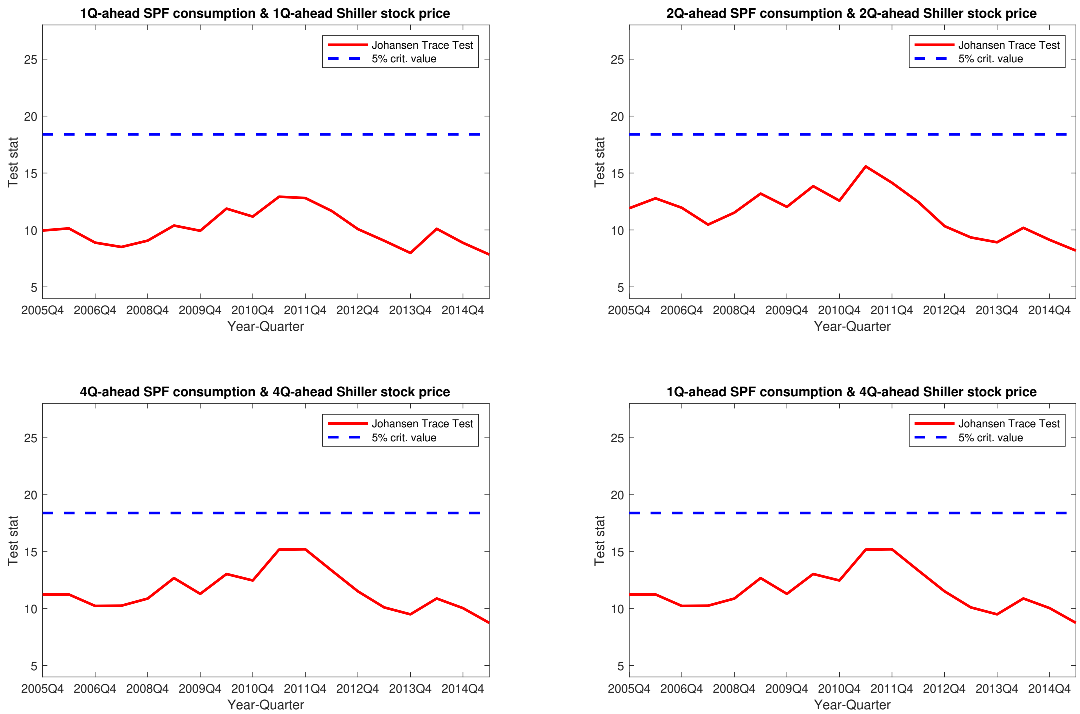


Figure A.10: Recursive Johansen Trace test for individual-level forecasts (ID:378)