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Industry bubbles and unexpected consumption shocks: A cross-sectional explanation of stock returns under recursive preferences

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ABSTRACT

Assuming an environment with rational and informed agents, where investors exhibit recursive preferences and make their economic decisions embedding industry bubbles into their information sets, we study to what extent unexpected consumption shocks can proxy for revisions in expected consumption growth and, consequently, explain the cross-sectional behavior of stock returns. Our results show that unexpected consumption shocks help forecast future consumption growth, allowing the Epstein-Zin model to satisfactorily explain the equity risk premium of different anomaly portfolios on the Tokyo Stock Exchange. Furthermore, our model provides a better understanding on the dynamics of consumption and its relationship to stock returns.

1. Introduction

The task of relating macroeconomics and asset prices has traditionally required dealing with problems that arise from the simplistic nature of some broadly-used utility functions —as is the case of the power-utility framework— and the complexity of more sophisticated non-separable utility functions, such as those based on consumer habits (Abel, 1990, 1999; Campbell & Cochrane, 1999; Constantinides, 1990) or recursive preferences (Epstein & Zin, 1989, 1991). Particularly, the power utility function directly sets the elasticity of intertemporal substitution (EIS) to the reciprocal of relative risk aversion (RRA), thus hindering the ability of the model to realistically explain both the risk-free rate and the equity risk premium (Weil, 1989). On the other hand, the preferences proposed by Epstein-Zin explicitly disentangle the EIS and the RRA coefficient, significantly increasing the versatility of consumption-based asset pricing at the cost of introducing revisions in expected utility as a key determinant of marginal utility.

The fact that shocks in expected consumption growth largely determine the explanatory power of the Epstein-Zin model implies that consumption dynamics are crucial for recursive utility to provide a satisfactory explanation for asset prices. Indeed, in the specific case that consumption growth is independent and identically distributed (i.i.d.) the Epstein-Zin environment is observationally equivalent to the power utility framework (Kocherlakota, 1990). In this context, it should be noted that consumption growth is one of the most unforecastable macroeconomic time series (Cochrane, 2008, p. 284). Hence, although Bansal and Yaron (2004) find that a small long-run predictable component in consumption growth together with fluctuating consumption volatility helps to largely explain

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important stylized facts in asset pricing, Parker and Julliard (2005) show that market returns provide poor estimates for future consumption growth. Remarkably, Pastor and Veronesi (2009) and Johannes et al. (2016) adopt a Bayesian approach to analyze the macroeconomic learning process, assuming that economic agents ignore the underlying model structure, but they learn about it by observing data. The authors show that counter-cyclical conditional volatility in beliefs about long-run dynamics significantly improves the ability of asset pricing models to explain asset returns.

On this basis, in this paper we exploit the relationship between industry bubbles and expected consumption growth to propose a model where revisions in expected consumption growth are measured by the unexpected shocks in consumption growth that result from the model developed by Rojo-Suárez et al. (2021), based on the Martin and Ventura (2012) setup. Specifically, building on the economic growth model with financial frictions and bubbles conditional on changes in investor sentiment suggested by Martin and Ventura (2012), Rojo-Suárez et al. (2021) show that the bubble terms that result from the Campbell and Shiller (1988) return identity for different industry portfolios help to largely explain the cross-sectional variation of expected consumption growth across countries. In particular, the authors show that technology bubbles and, especially, construction bubbles satisfactorily contribute to explain the expected consumption growth of nine European countries. Accordingly, we assume a representative agent setup to study the extent to which the fraction of consumption growth that remains unexplained by the Rojo-Suárez et al. (2021) model, as a proxy for revisions in expected consumption growth, allows the Epstein-Zin model to correctly explain stock returns on the Japanese equity market. For that purpose, we evaluate the performance of the model on three sets of anomaly portfolios comprising all stocks traded on the Tokyo Stock Exchange, for the period from July 1983 to June 2018.

Our paper contributes to the literature that analyzes the interplay between asset prices and macroeconomics, as well as the dynamics of consumption growth. Specifically, our paper provides three main contributions to the topic under study. First, to the best of our knowledge, this is the first study to examine the effect of industry bubbles on stock returns using the Epstein-Zin model to account for changes in expected consumption growth, contributing to fill the gap on the relationship between asset bubbles and asset prices. Although previous research emphasizes the strong influence of housing and stock bubbles on economic growth (Basco, 2014, 2016; Olivier, 2000; Simo-Kengne et al., 2015), industry bubbles have been rarely used to determine shifts in future consumption growth in explaining equity returns. Second, our research is the first to analyze the explanatory power of unexpected shocks in consumption growth in an environment with financial frictions, where rational and informed agents adopt their consumption and investment decisions considering explicitly bubbly episodes occurred across industries. Indeed, our research shows that when investors adopt their economic decisions embedding technology and construction bubbles into their information sets, unexpected shocks in consumption growth forecast future consumption growth at different horizons, allowing consumption-based asset pricing models to significantly improve their performance. Third, to the best of our knowledge, this is the first study to parameterize the bubble term in the Campbell and Shiller (1988) return identity using the investment-capital ratio (hereinafter, I/K ratio), determined according to the Cochrane (1991) methodology, to track shifts in bubbly episodes over time.

Our results show that unexpected shocks on consumption growth, as provided by the Rojo-Suárez et al. (2021) model, allow the Epstein-Zin model to significantly improve its performance in relation to the case in which revisions in expected consumption growth are proxied by the return on the wealth portfolio. Furthermore, in most cases, the unexpected shocks that result from explicitly considering industry bubbles in estimating consumption growth lead the Epstein-Zin model to outperform the Fama-French three--factor model (Fama & French, 1993). Hence, our results show that technology and construction bubbles, determined by the parameterized version of the Campbell and Shiller (1988) return identity, translate into revisions in expected consumption growth that are highly explanatory of equity returns on the Tokyo Stock Exchange.

Hereafter, the paper proceeds as follows. Section 2 defines the model under study. Section 3 describes the data series. Section 4 discusses the results. Section 5 concludes the paper.

2. The model

Following Lucas (1978) and Breeden (1979), the investor's first-order condition allows relating asset prices and investors' marginal utility $U_t^{'}$ as follows:

$$P_t = E_t\left[\beta \frac{U_t^{'}(C_{t+1})}{U_t^{'}(C_t)} X_{t+1}\right] = E_t(M_{t+1}X_{t+1}) \tag{1}$$

where P_t is the price at time t, $E_t(\cdot)$ is the expectation conditional on time-t information, β is the subjective discount factor, C_t is the consumption at time t, X_{t+1} is the asset payoff at time $t+1$, and M_{t+1} is the stochastic discount factor (SDF) or pricing kernel. Particularizing Equation (1) to the space of excess returns —i.e. payoffs with zero price, which represent a long position in an asset that is funded with a short position in another asset—, the expected excess return $E_t(R^e_{t+1})$ satisfies:

$$E_t\left(R^e_{t+1}\right) = -R^f_{t+1}\text{cov}_t\left(M_{t+1}, R^e_{t+1}\right) \tag{2}$$

where R^f_{t+1} is the risk-free rate or zero beta rate. In this framework, based on the theoretical framework defined by Kreps and Porteus (1978), Epstein and Zin (1991) develop their classic utility function:

$$U_t = \left\{ (1-\beta)C_t^{1-\frac{1}{\psi}} + \beta\left[E_t\left(U_{t+1}^{1-\gamma}\right)\right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}}$$

$$= \left\{ (1-\beta)C_t^{\frac{1-\gamma}{\theta}} + \beta\left[E_t\left(U_{t+1}^{1-\gamma}\right)\right]^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}} \tag{3}$$

where ψ is the EIS coefficient, γ is the RRA coefficient, and $\theta \equiv (1-\gamma)/(1-1/\psi)$. Equation (3) implies that investors' preferences are non-separable across states of nature, giving rise to the following SDF:

$$M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}} \left[\frac{U_{t+1}}{E_t\left(U_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}}\right]^{\frac{1}{\psi}-\gamma} \tag{4}$$

Remarkably, Equation (4) converges to power utility when $\theta = 1$, that is, when the RRA coefficient is equal to the reciprocal of EIS. In that case:

$$M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} \tag{5}$$

Given the unobservable nature of continuation utility in the second factor on the right-hand side of Equation (4), the intertemporal budget constraint for a representative agent in a complete-market environment allows Epstein and Zin (1991) to write Equation (4) as a function of the return on the wealth portfolio. Specifically, given the following intertemporal budget constraint:

$$W_{t+1} = R_{t+1}^W (W_t - C_t) \tag{6}$$

where W_{t+1} is the representative agent's wealth at time $t+1$ and R_{t+1}^W is the gross return on the wealth portfolio, Equation (4) can be rewritten as follows:

$$M_{t+1} = \left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\right]^{\theta} \left(\frac{1}{R_{t+1}^W}\right)^{1-\theta} \tag{7}$$

Under the assumption that asset returns and consumption are homoskedastic and jointly lognormal, Equation (7) allows us to write the expected excess return in Equation (2) as follows, with lowercase letters denoting logs:

$$E_t\left(r_{t+1}^i\right) - r_{t+1}^f + \frac{\sigma^2\left(r_{t+1}^i\right)}{2} = \theta\frac{\operatorname{cov}\left(\Delta c_{t+1}, r_{t+1}^i\right)}{\psi} + (1-\theta)\operatorname{cov}\left(r_{t+1}^W, r_{t+1}^i\right) \tag{8}$$

where r_{t+1}^i denotes the log return on asset i. Equation (8) shows that the Epstein-Zin utility function together with the intertemporal budget constraint adds an extra term to the classic consumption-based asset pricing framework, given by the covariance between the return on asset i and the return of the wealth portfolio. However, as noted by Campbell (2018, p. 180), the intertemporal budget constraint in Equation (6) implies that the terms $\operatorname{cov}(\Delta c_{t+1}, r_{t+1}^i)$ and $\operatorname{cov}(r_{t+1}^W, r_{t+1}^i)$ in Equation (8) are correlated, restricting the explanatory power of the model. Restoy and Weil (2011) overcome this limitation log-linearizing the intertemporal budget constraint to rewrite Equation (8) as follows:

$$E_t\left(r_{t+1}^i\right) - r_{t+1}^f + \frac{\sigma^2\left(r_{t+1}^i\right)}{2} = \gamma\operatorname{cov}\left(\Delta c_{t+1}, r_{t+1}^i\right) + \left(\gamma - \frac{1}{\psi}\right)\operatorname{cov}\left(g_{t+1}, r_{t+1}^i\right) \tag{9}$$

where $\operatorname{cov}(g_{t+1}, r_{t+1}^i)$ is the covariance of the revisions in expected consumption growth with the return on asset i. At this point, it should be noted that the Restoy and Weil (2011) specification, as well as the Epstein and Zin (1991) setup itself, imply important differences with respect to other models that account for news about future consumption growth, such as the intertemporal capital asset pricing model (ICAPM), proposed by Merton (1973). In this framework, the ICAPM represents a particularization of the classic consumption-based model, in which news about future consumption growth are assumed to influence current consumption growth, meaning that the return on the wealth portfolio together with different state variables that reflect news about future investment opportunities can track the investor marginal utility that results from current consumption. In contrast, the Epstein and Zin (1991) model explicitly isolates the effect on asset prices of news about future consumption that are *not yet* reflected on current consumption, meaning that consumption growth together with other variables that exhibit some predictive power to forecast consumption growth allow the model to explain asset prices. As noted, this fact implies that the Epstein and Zin (1991) model converges to the classic consumption-based framework in the case that consumption growth is i.i.d. Despite this, interestingly, Campbell (1993) suggests substituting consumption out of the Epstein and Zin (1991) model to get a discrete-time version of the ICAPM. Furthermore, Barroso et al. (2021) note that, under non-time separable preferences, changes in variables that capture news about future consumption growth should have explanatory power for stock returns in the ICAPM, even controlling for current consumption growth, which establishes a direct relationship between the ICAPM and the Epstein and Zin (1991) model.

In this context, any proxy for g_{t+1} should forecast future consumption growth $\sum_{j=2}^{T} \Delta c_{t+j}$. As shown below, the unexpected shocks in consumption growth that result from the Rojo-Suárez et al. (2021) model share this feature. Specifically, following Martin and Ventura (2012), the authors consider an environment with rational and informed agents, where the output of the economy is generated by a Cobb-Douglas production function, and economic agents are divided into productive and unproductive investors. Hence, in the environment defined by Martin and Ventura (2012), the economy fluctuates between a fundamental state, characterized by the absence of bubbly episodes, and a bubbly state, in which the economy is affected by bubbles created by productive and unproductive investors.

Importantly, Rojo-Suárez et al. (2021) introduce two major differences with respect to the Martin and Ventura (2012) setup. First, while Martin and Ventura (2012) distribute the bubble ownership across investors, assuming that young agents invest and old agents consume, Rojo-Suárez et al. (2021) assume that these roles are distributed globally across countries. Second, Rojo-Suárez et al. (2021) explicitly use risk loadings on bubbly episodes for specific industries to estimate consumption growth, and consequently explain expected consumption growth as a function of risk loadings and the prices of risk that result from the cross-sectional regression of expected consumption growth across countries on risk loadings.

On this basis, following the methodology described by Colacito and Croce (2013) and Colacito et al. (2018) to determine growth news shocks, we exploit the explanatory power of the Rojo-Suárez et al. (2021) model in estimating the expected consumption growth to forecast future consumption growth according to the following expression:

$$\Delta C_{t+1} = a + \mathbf{b}^{'} \Delta \mathbf{B_t} + c \Delta C_t + \varepsilon_{t+1} \tag{10}$$

where $\Delta \mathbf{B_t}$ is the variation rate of industry bubbles, determined as shown below, a, $\mathbf{b}$ and c are regression coefficients of domestic consumption growth on the explanatory variables, and ε_{t+1} is the error term.

We follow Rojo-Suárez et al. (2021) to determine industry bubbles $\mathbf{B_t}$ by parameterizing the bubble term in the Campbell and Shiller (1988) return identity using the I/K ratio. Specifically, for each industry k, the second term on the right-hand side of Equation (10) —i.e. the bubble term— is measured as follows:

$$B_t^{(k)} = \rho \left(\beta_2^{(k)} + \beta_3^{(k)} ik_t \right) \tag{11}$$

where $\rho = 1/(1 + DP)$, DP is the dividend yield, ik_t is the I/K ratio in logs, and $\beta_2^{(k)}$ and $\beta_3^{(k)}$ are the slope coefficients of the parameterized version of the AR(1) process for the dividend yield, as follows:

$$dp_{t+1}^{(k)} = \left(\beta_0^{(k)} + \beta_1^{(k)} ik_t \right) + \left(\beta_2^{(k)} + \beta_3^{(k)} ik_t \right) dp_t^{(k)} + \varepsilon_{t+1}^{(k)} \tag{12}$$

Remarkably, previous research analyzes bubble formation from a variety of perspectives. For example, Greenwood et al. (2019) show that different attributes of price run-ups, such as volatility, turnover, or the price path of the run-up, can help forecast potential crashes. In contrast, other research emphasizes the importance of the relationship between bubbly episodes and investment, as measured by the I/K ratio, to identify bubbles. Thus, Chirinko and Schaller (2001) build on the orthogonality tests pioneered by Hall (1978), to explicitly relate investment and bubbles in the Japanese equity market, concluding that bubbles exhibit a statistically significant relationship with the I/K ratio. Furthermore, using a nonstructural forecasting equation that controls for macroeconomic factors which might affect investment, Chirinko and Schaller (2001) find that the I/K ratio is about 20 percent higher than predicted by these factors in the late 1980's —a period of exacerbated market boom in Japan—, but lower than predicted following the crash.

In order to endogenously generate ik_t series in Equations (11) and (12) using gross private domestic investment, we follow the Cochrane (1991) approximation for the I/K ratio, which satisfies:

$$\frac{I_{t+1}}{K_{t+1}} = \frac{I_{t+1}}{I_t} \frac{I_t/K_t}{(1-\delta)\left[1 + (I_t/K_t) - (\alpha/2)(I_t/K_t)^3\right]} \tag{13}$$

where δ is the depreciation rate and α is the adjustment cost parameter. Importantly, Equations (10)–(13) allow us to proxy the revisions in expected future consumption growth g_{t+1} in Equation (9) by the unexpected shocks in consumption growth ε_{t+1} that result from Equation (10). Below we show that ε_{t+1} is highly predictive of future consumption growth, helping to significantly improve the explanatory power of the classic consumption-based asset pricing framework.

3. Data and unexpected consumption shocks

In order to study the behavior of the Epstein and Zin-based model in Equation (9) when revisions in expected consumption growth are proxied by the shocks in consumption growth that result from Equation (10), below we analyze its performance in relation to that of the classic derivation of Epstein and Zin (1991) in Equation (8), as well as other classic asset pricing models, namely, the capital asset pricing model (CAPM), the consumption-CAPM (CCAPM) and the Fama-French three- and five-factor models. Accordingly, in this present section we explain all data series used in this study and analyze the main statistical properties of consumption shocks in Equation (10), while the next section describes and discusses model results.

3.1. Data

We evaluate model performance on different sets of anomaly portfolios that comprise all stocks traded on the Tokyo Stock Exchange, for the period from July 1983 to June 2018. At this point, it should be noted that the specific demographic conditions of Japan help to partly explain falling prices and lower output since 1990, which ultimately results in deflation and yen appreciation (Anderson et al., 2014; Sanchez & Yurdagul, 2014). This fact, together with the peculiarities of construction and technology sectors in Japan, has made us consider it appropriate to evaluate model performance on the Japanese equity market.

We compile all stock data from the Datastream database and fully process all data series used in this research. Specifically, we collect the following data series from Datastream, on a monthly basis: (i) total return index (RI series), (ii) market value (MV series), (iii) market-to-book equity (PTBV series), (iv) total assets (WC02999 series), (v) return on equity (WC08301 series), (vi) tax rate (WC08346 series), (vii) dividend yield (DY series), (viii) price-to-cash flow ratio (PC series), and (ix) primary SIC codes. We use the filters suggested by Griffin et al. (2010) for Datastream series to exclude special purpose vehicles from data. Consequently, our sample comprises 3866 stocks, considering all companies that made initial public offerings or that were delisted in the period under study, which allows us to mitigate the survivorship bias in the sample.

We use the Datastream series to generate three sets of portfolios, which constitute our test assets. First, we form 25 portfolios sorted by size and book-to-market equity (hereinafter size-BE/ME portfolios) following the Fama and French (1993) methodology. In particular, at the end of June of each year we allocate all stocks to quintiles based on their market value and, analogously, we allocate stocks in an independent sort to five BE/ME groups. Size-BE/ME portfolios are determined as the intersections of the size and BE/ME groups. We use the market equity at the end of June to determine value-weighted returns on a monthly basis. Second, we form 25 portfolios sorted by size and dividend yield (hereinafter size-DY portfolios) using the same methodology. Third, we follow the same procedure to form 25 portfolios sorted by size and the price-to-cash flow ratio (hereinafter size-PC portfolios). We determine excess returns using the three-month Treasury Bill rate for Japan, as provided by the OECD database, as a proxy for the risk-free rate. Finally, we determine the Fama-French factors following the methodology described in Fama and French (1993) and Fama and French (2015),

Table 1
Summary statistics.

Panel A: 25 size-BE/ME										
	Low	2	3	4	High		Low	2	3	4	High
	Means						St. Dev.				
Small	8.48	9.19	8.37	5.88	5.78	Small	23.75	21.70	24.82	15.84	14.38
2	4.80	4.51	4.31	4.18	5.51	2	19.53	16.66	14.73	13.41	14.44
3	4.53	3.45	3.24	3.45	4.64	3	22.04	13.80	13.24	12.98	13.90
4	2.20	2.45	2.97	3.57	3.79	4	14.86	12.46	11.67	11.66	12.75
Big	1.22	2.47	3.09	3.03	3.45	Big	12.71	12.49	10.98	10.92	12.61
Panel B: 25 size-DY portfolios											
	Low	2	3	4	High		Low	2	3	4	High
	Means						St. Dev.				
Small	8.90	5.36	6.27	4.10	4.50	Small	24.66	17.30	19.52	12.91	13.96
2	4.65	2.97	3.45	3.54	3.87	2	17.49	13.27	12.43	12.32	12.30
3	4.42	2.34	3.01	2.69	3.60	3	21.73	12.02	12.06	11.73	12.90
4	2.72	1.95	2.09	2.50	2.82	4	15.45	10.55	10.36	11.32	12.08
Big	1.23	2.15	2.17	2.11	2.47	Big	11.35	11.85	10.76	10.74	10.72
Panel C: 25 size-PC portfolios											
	Low	2	3	4	High		Low	2	3	4	High
	Means						St. Dev.				
Small	8.26	6.24	6.89	5.62	6.14	Small	22.16	16.65	18.03	19.11	21.92
2	4.88	5.48	4.77	3.83	3.81	2	17.83	14.72	13.63	13.44	17.20
3	5.47	4.97	3.87	2.94	2.12	3	21.17	13.68	12.66	13.07	15.19
4	3.70	4.31	3.11	2.41	1.50	4	15.35	11.72	11.46	11.43	13.38
Big	2.36	2.27	2.03	2.14	1.69	Big	13.09	10.72	11.73	12.26	12.76

Panel D: Market factors and macroeconomic series									
	RMRF	*SMB*	*HML*	*RMW*	*CMA*		ΔC		*g*
Means	2.34	2.60	0.90	2.56	−3.33	Means	0.26	Means	0.00
St. Dev.	11.20	8.55	6.28	6.22	5.56	St. Dev.	2.37	St. Dev.	1.59

Notes: We compile monthly series from the Datastream database for all stocks traded on the Tokyo Stock Exchange, for the period from July 1983 to June 2018. We use these data to form three sets of portfolios following the Fama and French (1993) methodology, namely: (i) 25 portfolios size-BE/ME, (ii) 25 portfolios size-DY, and (iii) 25 portfolios size-PC. In order to determine excess returns, when appropriate we use the three-month Treasury Bill rate for Japan. We compile quarterly private final consumption expenditure for Japan, as provided by the OECD. All results are determined on a quarterly basis. Means and standard deviations are percentages.

which allows us to generate the following time series: (i) RMRF (the return of the value-weighted market portfolio minus the risk-free rate), (ii) SMB (the small minus big market value factor), (iii) HML (the high minus low book-to-market equity factor), (iv) RMW (the excess return of the most profitable stocks minus the least profitable), and (v) CMA (the excess return of companies that invest conservatively minus aggressively). All return data are publicly available at Rojo-Suárez and Alonso-Conde (2022).

In order to ensure consistency with the periodicity of consumption data, we compound monthly return series to determine quarterly returns. Table 1 shows average returns and standard deviations for the portfolios and factors under consideration. Panels A–C in Table 1 show that the size effect works as expected, with portfolios comprising small firms providing higher average returns, and vice versa. In contrast, Panel A in Table 1 shows that the value effect —that is, the fact that higher BE/ME ratios are often accompanied by higher expected returns, and vice versa— exhibits a more irregular pattern, with only portfolios in the fourth and fifth size quintiles fitting the classic pattern, consistent with the sharp reduction in the value premium experienced by other equity markets, as noted by Cochrane (2005, p. 452).

On the other hand, Panel B in Table 1 shows that, when we ignore the first DY quintile, in general, the higher the dividend yield, the higher the average return, and vice versa. Furthermore, Panel C in Table 1 shows that expected returns are inversely related to the price-to-cash flow ratio. Hence, the patterns followed by average returns across dividend yield and price-to-cash flow quintiles are consistent with most ratios that scale asset prices by some variable, where relatively low market prices often translate into high expected returns, and vice versa. Regarding factors, Panel D in Table 1 shows that the average return for RMRF amounts to 2.34%, which is in line with the returns provided by other stock markets.

We compile all macroeconomic data from the OECD Statistics section. Regarding consumption data, although the CCAPM establishes the consumption growth in nondurable goods and services as the only explanatory variable for asset prices, the Epstein-Zin model requires considering all components of consumption, since the non-separability across states of nature introduces a non-separability across goods (Cochrane, 2008, p. 285). Furthermore, Parker and Julliard (2005) show that final consumption data provide lower pricing errors than consumption in nondurables and services when estimating expected returns of size-BE/ME portfolios. Hence, we use total consumption data ('Private final consumption expenditure' series, CQR measure), as well as the population series for Japan, as provided by the OECD Statistics section, to determine per capita consumption growth. As shown in Table 1 Panel D, the average consumption growth for Japan in the period under study is 0.26% on a quarterly basis, while its standard deviation amounts to 2.37%.

3.2. *Unexpected consumption shocks*

In order to estimate unexpected consumption shocks in Equation (10), we first generate ik_t in Equation (13) using quarterly gross capital formation series, in national currency, seasonally adjusted, as provided by the OECD. Following Cochrane (1991), we assume a value of 0.1 for δ, and we set the I/K ratio at the beginning of the period under study to the fixed point in Equation (13) that equals investment growth to its mean value. We assume no adjustment costs, so that $\alpha = 0$. On the other hand, we use Datastream data series

Table 2
Predictive power analysis of industry bubbles on consumption growth.

Panel A: Quarterly results					
Lag size	Intercept	ΔB_t^C	ΔB_t^T	ΔC_t	R^2
1 quarter	.005 (3.917)	−57.504 (-3.821)	−67.443 (-3.878)	−.723 (-14.404)	.512
Panel B: Annual results					
Lag size	Intercept	ΔB_t^C	ΔB_t^T	ΔC_t	R^2
1 year	.003 (1.352)	−15.714 (-4.493)	−17.976 (-4.365)	.641 (5.762)	.389
2 years	.008 (1.949)	−16.165 (-1.770)	−18.593 (-1.711)	1.040 (5.060)	.270
3 years	.014 (2.452)	−9.443 (-.625)	−10.176 (-.571)	1.509 (5.259)	.226
4 years	.016 (2.213)	−19.890 (-1.248)	−21.525 (-1.139)	2.016 (5.097)	.230

Notes: The table shows the estimates that result from the forecasting regression of consumption growth on the lagged growth rate of construction and technology bubbles and consumption growth. Columns labeled ΔB_t^C and ΔB_t^T show the slope coefficients of the construction and technology bubbles, respectively, determined by the AR(1) process of the value-weighted dividend yield for each industry, using the I/K ratio to parameterize model coefficients. All t-statistics are in parentheses and are corrected for the autocorrelation that results from overlapping consumption growth rates in Panel B, following the Hansen and Hodrick (1980) methodology. The column labeled R^2 shows adjusted R^2 statistics.

to form two value-weighted industry portfolios comprising the dividend yield for the construction and technology sectors, as defined by Rojo-Suárez et al. (2021). Specifically, following the authors, we use two-digit SIC codes number 15 and 17 for construction, and codes number 36 and 48 for technology.

Both ik_t and dividend yield series allow us to generate bubble terms in Equation (10) using Equations (11) and (12). We use these bubble terms to estimate the coefficients in Equation (10) and consequently determine the unexpected shocks in consumption growth ε_{t+1}. Table 2 shows the regression results for Equation (10) using both quarterly and annual data periodicity. Additionally, in order to analyze the extent to which the model allows the estimates to track actual consumption growth, Fig. 1 plots consumption growth and the forecasts that result from Equation (10).

Table 2 shows that Equation (10) contributes significantly to forecast future consumption growth, providing an adjusted R^2 statistic of 51.2% at 1-quarter horizon, and adjusted R^2 statistics ranging from 22.6% to 38.9% at different annual horizons. These results are similar to those obtained by Rojo-Suárez et al. (2021), who find R^2 statistics ranging from 21.2% to 60.8% for nine developed countries, using contemporary consumption growth as the dependent variable and world consumption growth as additional explanatory variable.

Table 2 also shows that model coefficients are strongly significant at 1-quarter and 1-year horizon, meaning that both industry bubbles and past consumption growth exhibit strong predictive power for future consumption growth. Fig. 1 is consistent with this fact, showing that the fitted values that result from Equation (10) closely track actual consumption growth for most of the years under study. In particular, the plot on the left-hand side of Fig. 1 relates the demeaned values of actual consumption growth to the forecasts that result from the bubble term in Equation (10), showing that both lines follow a similar pattern in the periods 1986–1996 and 2009–2013. Additionally, the plot on the right-hand side in Fig. 1, which adds the term comprising lagged consumption growth to the bubble term (see Equation (10)), shows that past consumption growth significantly helps improve the predictive power of the model.

Importantly, the fact that we use the error term ε_{t+1} in Equation (10) as a proxy for revisions in expected consumption growth g_{t+1} in Equation (9) leads us to explicitly assume that $\mathrm{cov}(g_{t+1}, r^i_{t+1}) = \mathrm{cov}(\varepsilon_{t+1}, r^i_{t+1})$. Therefore, in order to analyze the predictive power of g_t as proxied by ε_t, Table 3 shows the results obtained for different forecasting regressions using annual revisions in expected consumption growth as a predictor. Specifically, Panel A in Table 3 shows the regression results for the AR(1) process of g_t at different lags, while Panel B examines the predictive power of g_t in estimating future compounded consumption growth.

The results in Table 3 Panel A show that, in general, consumption shocks g_t are not persistent, with only 5-year estimates providing a statistically significant slope coefficient and a R^2 statistic greater than 10%, consistent with the autocorrelation and partial autocorrelation functions shown in Fig. 2 for g_t. However, Panel B in Table 3 shows that positive shocks in consumption growth predict increasingly positive compounded consumption growth as the time interval expands, with the slope coefficient increasing from 0.714 for 1-year forecasts to 3.545 at an 8-year horizon. Remarkably, all slopes are statistically significant except for 5-year forecasts. Furthermore, the R^2 statistic amounts to 28.5% at a 1-year horizon, decreasing for longer horizons to reach a minimum at the 5-year horizon, and increasing thereafter to 25.3% for 8-year forecasts. Importantly, these correlations are of the same order of magnitude than those typically achieved by other predictive regressions used to forecast equity returns and consumption growth (see Cochrane (2011) and Ludvigson (2004), respectively), and exhibit a specific horizon length-dependent pattern, consistent with the research by Parker and Julliard (2005).

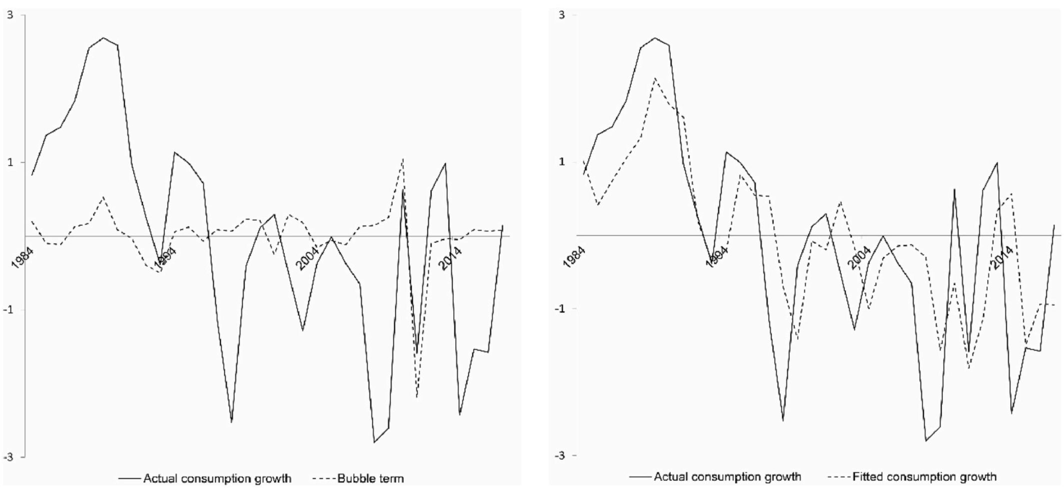
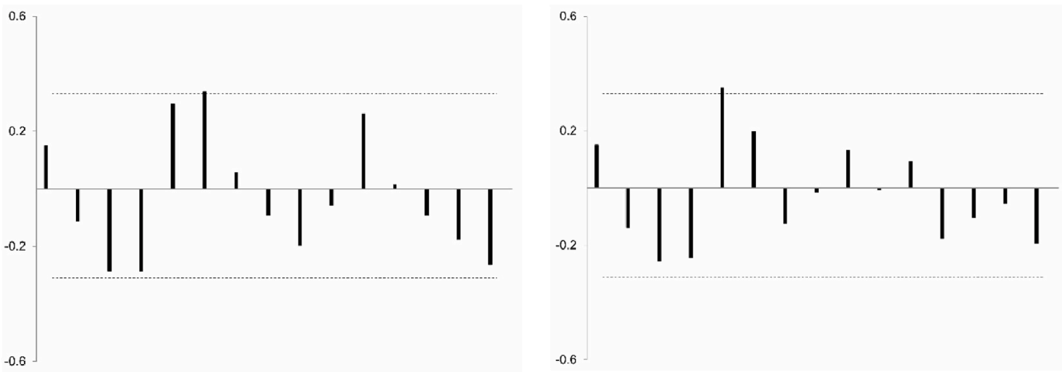


Fig. 1. Actual consumption growth and predicted values.
Notes: The figure relates the demeaned values of actual consumption growth to the forecasts that result from the regression of consumption growth on the lagged growth rate of construction and technology bubbles —ΔB^C_t and ΔB^T_t, respectively— and lagged consumption growth. Thus, the plot on the left-hand side isolates the predictive power of the bubble term, determined by $b_1 \Delta B^C_t + b_2 \Delta B^T_t$, where b_1 and b_2 are regression coefficients. The plot on the right-hand side adds the term comprising lagged consumption growth $c\Delta C_t$ to the bubble term, where c is a regression coefficient. Both actual consumption growth and its predicted value are aligned to the same time interval for better comparison.

Table 3
Predictive power analysis of revisions in expected consumption growth.

Panel A: AR(1) process for consumption shocks $g_{t+k} = a + bg_t + \varepsilon_{t+k}$				
	1 year	2 years	5 years	8 years
Slope	.160	−.114	.422	−.160
	(1.162)	(-.620)	(1.960)	(-.991)
R^2	.025	.013	.145	.018
Panel B: Consumption growth forecasting regressions $\prod_{j=1}^{k}(1 + \Delta C_{t+j}) = a + bg_t + \varepsilon_{t+k}$				
	1 year	2 years	5 years	8 years
Slope	.714	1.066	1.386	3.545
	(4.191)	(3.590)	(1.826)	(3.242)
R^2	.285	.200	.074	.253

Notes: The table shows the results of different forecasting regressions using annual revisions in expected consumption growth g_t as a predictor, where t-statistics are in parentheses. Panel A shows the regression results provided by the AR(1) process for g_t at different lags, while Panel B shows the regression results provided by g_t in forecasting future compounded consumption growth. We correct the standard errors used to determine t-statistics for the autocorrelation that results from overlapping consumption growth rates in Panel B, following the Hansen and Hodrick (1980) methodology.



(a) Autocorrelation function (b) Partial autocorrelation function

Fig. 2. Autocorrelation and partial autocorrelation functions for g_t.
Notes: The figure shows the autocorrelation and partial autocorrelation functions for annual revisions in expected consumption growth g_t, as proxied by the error term of the forecasting regression of future consumption growth on the growth rate of construction and technology bubbles and consumption growth.

Fig. 3 provides further insight on the patterns followed by both the R^2 statistic and the slope coefficient in Table 3 Panel B at different horizons. These results provide proof of the predictive power of consumption shocks in Equation (10) for future consumption growth and, therefore, current revisions in expected consumption growth. Accordingly, in the next section we analyze the extent to which these consumption shocks allow the Epstein-Zin model to explain the cross-sectional behavior of stock returns on the Tokyo Stock Exchange.

4. Results and discussion

In this section we study the performance of the Epstein-Zin model in Equation (9) when revisions in expected consumption growth g_t are proxied by the shocks in consumption growth that result from Equation (10). Moreover, below we compare the performance of the model with that of the classic derivation of Epstein and Zin (1991) in Equation (8), as well as the CAPM, the CCAPM, and the Fama-French three- and five-factor models. We evaluate all models using their beta representations, as is usual in most empirical research on asset pricing. In particular, we use the following unconditional beta model:

$$\mathbf{E}\left(\mathbf{R}^{\mathbf{e}}_{\mathbf{t+1}}\right) = \beta_{\mathbf{f}}\lambda_{\mathbf{f}} \tag{14}$$

where $\mathbf{E}(\mathbf{R}^{\mathbf{e}}_{\mathbf{t+1}})$ is the N-dimensional vector of excess returns that constitute our test assets, $\beta_{\mathbf{f}}$ is the $N \times K$ matrix of betas, and $\lambda_{\mathbf{f}}$ is the K-dimensional vector of prices of risk. Depending on the model, the vector of factors $\mathbf{f}$ is defined as shown in Table 4.

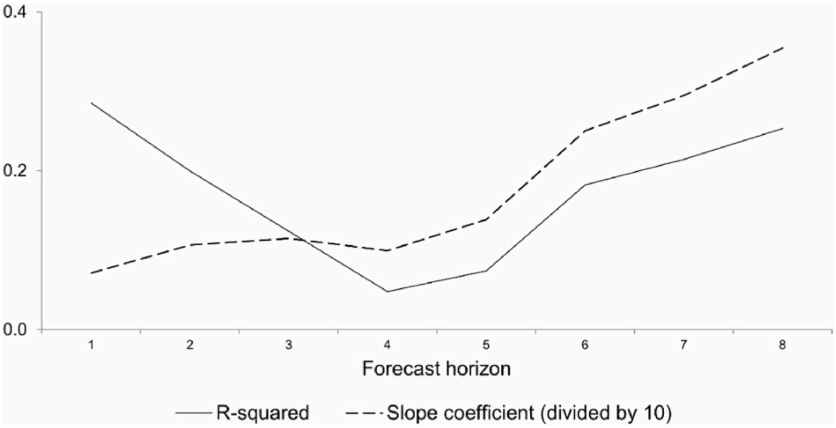


Fig. 3. Predictive power of shocks in consumption growth at different horizons.
Notes: The table shows the R^2 statistic and slope coefficient of the forecasting regression of consumption growth, using annual revisions in expected consumption growth g_t as a predictor.

Table 4
Explanatory factors of the models under analysis.

Model	ΔC	g	*RMRF*	*SMB*	*HML*	*RMW*	*CMA*
Epstein-Zin model (Restoy & Weil, 2011)	x	x					
Epstein-Zin model (Epstein & Zin, 1991)	x		x				
CAPM			x				
CCAPM	x						
Fama-French (3 factors)			x	x	x		
Fama-French (5 factors)			x	x	x	x	x

We estimate all models mapping the two-pass cross-sectional regression procedure (CSR) into the generalized method of moments (GMM), which allows us to simultaneously determine betas and lambdas in Equation (14). Specifically, we use the following moment restrictions:

$$\mathbf{g_T}(\mathbf{b}) = \left\{ \begin{array}{c} \mathbf{E}\left(\mathbf{R}_t^e - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t\right) \\ \mathbf{E}\left[\left(\mathbf{R}_t^e - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t\right)\mathbf{f}_t\right] \\ \mathbf{E}\left(\mathbf{R}_t^e - \boldsymbol{\beta}\boldsymbol{\lambda}\right) \end{array} \right\} \tag{15}$$

where **a** is the vector of intercepts of the time-series regressions. We estimate standard errors using a spectral density matrix with zero leads and lags, correcting for cross-sectional correlation and for the fact that betas are generated regressors. Table 5 shows the regression results for all models.

We evaluate model performance using the R^2 statistic, the mean absolute error (MAE) and the *J*-test for overidentifying restrictions (Hansen, 1982). Regarding the R^2 statistic, Table 5 shows both adjusted ordinary least squares (OLS) and unadjusted generalized least squares (GLS) estimates, in that order, for each model, consistent with Lewellen et al. (2010). According to Lewellen et al. (2010), the GLS R^2 statistic is directly related to the mean-variance efficiency of the factor-mimicking portfolio, while this relationship is essentially spurious in the case of the OLS R^2 statistic. Consequently, the authors strongly recommend analyzing both statistics in asset pricing model evaluation.

Table 5 shows that, in most cases, the revisions in expected consumption growth that result from unexpected consumption shocks in Equation (10) allow the Epstein-Zin model to significantly improve its performance relative to the case in which expected shifts in investors' utility are proxied by the return on the wealth portfolio, as measured by RMRF. In particular, the results of the Epstein-Zin model in rows 1 and 7 of Table 5 show that, for size-BE/ME and size-DY portfolios, shocks in consumption growth allow the model to outperform the other models, with the sole exception of the Fama-French five-factor model. Conversely, the results in Table 5 Panel C show that size-PC portfolios constitute a major hurdle for the model, translating into a similar performance for all consumption-based asset pricing models under analysis.

Regarding size-BE/ME portfolios, Panel A in Table 5 shows that g leads the Epstein-Zin model in row 1 to reach an adjusted OLS R^2 statistic and a MAE of 74.3% and 0.74%, respectively, while the classic Epstein-Zin model and the CCAPM (rows 2 and 4) provide an adjusted OLS R^2 statistic of 48.1% and 49.3%, and a MAE of 1.04% and 1.09%, respectively. Hence, the performance of the Epstein-Zin model in row 1 is similar to that achieved by the linear version of the ultimate consumption risk model proposed by Parker and Julliard (2005), which provides a R^2 statistic of up to 70% for 25 size-BE/ME portfolios comprising US-traded equities, although worse than

Table 5
Regression results for the models under analysis.

Row	Model	Intercept	Consumption gr.	Revisions in $E(\Delta C)$	Market factors					R^2	MAE (%)	J-test
			$\lambda_{\Delta C}$	λ_g	λ_{RMRF}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}			
Panel A: 25 size-BE/ME portfolio results												
1	Epstein-Zin model	.018	.002	.020						.743	.74	31.781
	Restoy and Weil (2011)	(1.236)	(.298)	(2.465)						.521		(.081)
2	Epstein-Zin model	.034	−.007		−.018					.481	1.04	56.532
	Epstein and Zin (1991)	(1.219)	(-.241)		(-2.903)					.117		(.000)
3	CAPM	−.032			.072					.301	1.24	64.868
		(-1.238)			(2.393)					.006		(.000)
4	CCAPM	.014	−.015							.493	1.09	64.408
		(1.356)	(-2.856)							.126		(.000)
5	Fama-French (3 factors)	−.025			.044	.031	.007			.712	.78	60.642
		(-.650)			(1.137)	(4.084)	(1.185)			.623		(.000)
6	Fama-French (5 factors)	−.028			.046	.027	.016	−.018	−.048	.817	.65	19.214
		(-.601)			(1.010)	(3.450)	(2.273)	(-.951)	(-2.639)	.760		(.443)
Panel B: 25 size-DY portfolio results												
7	Epstein-Zin model	.016	.006	.022						.843	.51	16.591
	Restoy and Weil (2011)	(1.160)	(.625)	(2.586)						.769		(.786)
8	Epstein-Zin model	.022	.004		−.021					.619	.78	31.468
	Epstein and Zin (1991)	(.739)	(.102)		(-2.274)					.360		(.087)
9	CAPM	−.039			.080					.453	.98	38.484
		(-1.731)			(2.665)					.335		(.023)
10	CCAPM	.010	−.019							.630	.80	37.261
		(.990)	(-2.755)							.355		(.031)
11	Fama-French (3 factors)	−.044			.069	.029	.007			.738	.62	31.473
		(-1.749)			(2.446)	(3.081)	(.647)			.653		(.066)
12	Fama-French (5 factors)	−.005			.025	.026	.011	−.036	−.031	.854	.45	17.243
		(-.155)			(.664)	(2.408)	(.840)	(-2.300)	(-1.462)	.727		(.573)
Panel C: 25 size-PC portfolio results												
13	Epstein-Zin model	.014	−.009	.007						.481	.99	101.760
	Restoy and Weil (2011)	(1.419)	(-1.682)	(1.672)						−.341		(.000)
14	Epstein-Zin model	.028	−.004		−.019					.474	.95	79.856
	Epstein and Zin (1991)	(1.326)	(-.171)		(-2.625)					−.354		(.000)
15	CAPM	−.015			.053					.172	1.36	112.146
		(-.868)			(2.507)					.066		(.000)
16	CCAPM	.010	−.017							.480	1.00	91.366
		(.954)	(-2.865)							−.286		(.000)
17	Fama-French (3 factors)	−.012			.031	.029	.009			.692	.77	91.791
		(-.738)			(1.647)	(3.754)	(1.174)			.582		(.000)
18	Fama-French (5 factors)	−.032			.052	.033	.005	.007	−.013	.703	.71	60.631
		(-1.596)			(2.330)	(4.249)	(.635)	(.598)	(-.791)	.564		(.000)

Notes: We compile monthly series for all stocks traded on the Tokyo Stock Exchange from the Datastream database, for the period from July 1983 to June 2018. Using these data, we form three sets of portfolios, namely: (i) 25 size-BE/ME portfolios, (ii) 25 size-DY portfolios, and (iii) 25 size-PC portfolios. We compound monthly return series to determine quarterly returns, thus ensuring consistency with the periodicity of consumption data. In order to determine excess returns, we use the three-month Treasury Bill rate for Japan. We map the two-pass CSR procedure into GMM to estimate all models, assuming a spectral density matrix with zero leads and lags. We use the same spectral density matrix to run the *J*-test. The table displays two rows for each model, where the first row shows the coefficient estimates and the second row the *t*-statistics. For each model, the columns labeled 'R^2' show the adjusted OLS and unadjusted GLS R^2 statistics, in that order, consistent with Lewellen et al. (2010). All *p*-values that result from the *J*-tests are in parentheses. All results are determined on a quarterly basis.

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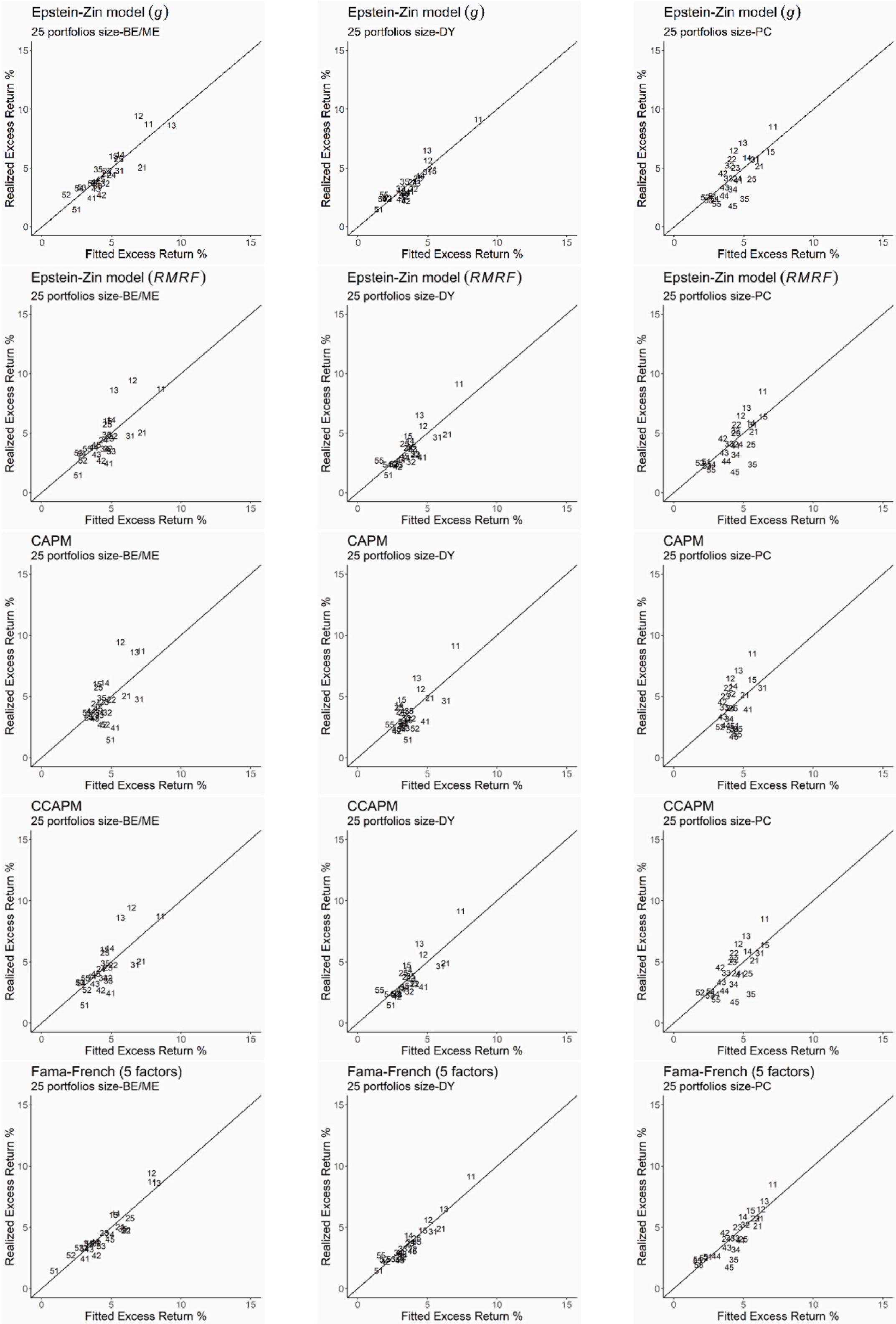

(caption on next page)

Fig. 4. Realized excess returns versus fitted values.
Notes: We plot size-BE/ME portfolios, size-DY portfolios and size-PC portfolios according to a code with two numbers, the first number being the size code (with 1 being the smallest and 5 the largest) and the second number being the BE/ME ratio, the DY ratio and the PC ratio codes, respectively (with 1 representing a low ratio and 5 a high ratio).

that of the durable consumption model under recursive preferences proposed by Yogo (2006), which provides a R^2 statistic of 93.5% for the same test assets.

As shown in Table 5, the Epstein-Zin model in row 1 performs very similarly to the Fama-French three-factor model in row 5. Moreover, the Epstein-Zin model in row 1 and the Fama-French five-factor model in row 6 are the only models in Panel A that are not rejected by the *J*-test for overidentifying restrictions. At this point, it is important to note that, under the specifications described above for our model evaluation procedure, the *J*-test for overidentifying restrictions is numerically equivalent to the test proposed by Gibbons et al. (1989) to evaluate asset pricing models, meaning that our result is consistent with that obtained by Fama and French (2017) for their five-factor model in pricing 25 Japanese size-BE/ME portfolios. However, it should be noted that the GLS R^2 statistic of the Fama-French three- and five-factor models is higher than that of the Esptein-Zin model in row 1, meaning that their factor-mimicking portfolios are closer to being mean-variance efficient.

Regarding pricing errors, Fig. 4 relates the average excess returns of the portfolios under analysis with the fitted values provided the models considered, where the closer the data points are to 45° axis, the lower the pricing errors, and vice versa. As shown, while both the Epstein-Zin model that explicitly accounts for revisions in expected consumption growth (g) and the Fama-French five-factor model provide quite similar pricing errors, the remaining models display more scattered plots, thus involving higher pricing errors.

Panel B in Table 5 shows that most of the patterns shown in Panel A for size-BE/ME portfolios persist for size-DY portfolios. Thus, revisions in expected consumption growth g help the Epstein-Zin model to increase the adjusted OLS R^2 statistic from 61.9% (row 8) to 84.3% (row 7) and reduce its MAE from 0.78% to 0.51%. Moreover, as in Panel A, the Epstein-Zin model in row 7 and the Fama-French five-factor model in row 12 clearly pass the *J*-test for overidentifying restrictions, yielding p-values greater than 50%. Regarding GLS R^2 statistics, size-DY portfolios lead the Epstein-Zin model in row 7 to outperform the other models under analysis. In particular, while this model provides an GLS R^2 statistic of 76.9%, the Fama-French three- and five-factor models in rows 11 and 12 provide GLS R^2 statistics of 65.3% and 72.7%, respectively, meaning that the factor-mimicking portfolio of the Epstein-Zin model in row 7 is closer to be mean-variance efficient. All these results are consistent with the pricing errors depicted in Fig. 4 for size-DY portfolios.

Finally, Panel C in Table 5 shows that most of the models perform significantly worse in explaining the expected returns of size-PC portfolios. Furthermore, in this case, both the Fama-French three- and five-factor models clearly outperform the Epstein-Zin model in row 13, providing adjusted OLS R^2 statistics close to 70%. Moreover, rows 13 and 14 in Table 5 show that revisions in expected consumption growth, as measured by g, and the return on the wealth portfolio, as proxied by RMRF, yield nearly identical results, making the Epstein-Zin model provide adjusted OLS R^2 statistics about 47%–48% and MAEs close to 1% in both cases. On the other hand, GLS R^2 statistics show that the factor-mimicking portfolios of consumption models in Panel C (rows 13, 14 and 16) are extraordinarily far from mean-variance efficient, which largely explains the worse performance of the models when pricing size-PC portfolios. Remarkably, the *J*-test for overidentifying restrictions rejects all models in Panel C.

Regarding model coefficients, it is important to note that the estimates for λ_g in Table 5 are significant for size-BE/ME and size-DY portfolios. Furthermore, these coefficients are positive for all portfolios under consideration, meaning that those stocks that covary positively with g will trade at relatively low prices or, equivalently, provide relatively high expected returns, consistent with Equation (9). Moreover, these results are also consistent with the positive slope coefficients shown in Table 3 Panel B for the forecasting regression of consumption growth on the revisions in expected consumption growth g. In particular, according to our model, a variation in g today signals a change in the same direction in expected consumption growth, implying that the higher the covariance between asset returns and g, the higher the expected return, and vice versa, consistent with the results of Parker and Julliard (2005).

Additionally, the results in Table 5 also allow us to analyze the value of the RRA and EIS coefficients in Equation (9) that implicitly result from $\lambda_{\Delta C}$ and λ_g estimates. In fact, Equations (9) and (14) imply that the RRA coefficient satisfies $\gamma \cong \lambda_{\Delta C} / \mathrm{var}(\Delta c_{t+1})$, while the EIS coefficient follows $\psi \cong 1/[\gamma - \lambda_g / \mathrm{var}(g)]$. Hence, using the statistics summarized in Table 1 to determine $\mathrm{var}(\Delta c_{t+1})$ and $\mathrm{var}(g)$, the $\lambda_{\Delta C}$ and λ_g estimates in Table 5 translate into a value for γ of 3.6 and 10.7 using the results in Panels A and B, respectively, and a value for ψ of -0.013 for both size-BE/ME and size-DY portfolios. Remarkably, our results for γ show that g allows the Epstein-Zin model to partially overcome the equity risk premium puzzle, as defined by Mehra and Prescott (1985), with the RRA coefficient that results from size-BE/ME portfolios being consistent with the general idea that risk aversion should be about 3–5, as noted by Cochrane (2005, p. 464). Furthermore, our estimates for γ are close to those obtained by Parker and Julliard (2005) when evaluating the linear version of their ultimate consumption risk model, assuming a constant risk-free rate under different estimation procedures.

Similarly, our estimate for ψ is consistent with the confidence intervals determined by Yogo (2004) for the Japanese EIS coefficient, as well as with the negative value achieved for ψ by a part of the related literature (see Havranek et al. (2015) for a comprehensive review on this particular). In any case, it is important to note that the estimates for the EIS coefficient reported by the literature vary substantially across studies. For example, using an approach based on the Japanese consumption tax rate, Cashin and Unayama (2016) find that, although the EIS in Japan amounts to 0.21, its value is not significantly different from zero. Hence, following Hall (1988), we can interpret the negative EIS provided by our model as the case where a significantly positive value for ψ can be rejected.

In sum, our results suggest that the unexpected shocks in consumption growth that result from an environment where rational investors explicitly embed construction and technology bubbles into consumption expectations significantly contribute to improve the performance of the Epstein-Zin model, for most of the portfolios under analysis. Moreover, our results show that unexpected consumption shocks help to forecast future consumption growth, which largely explains their high explanatory power in estimating the expected excess returns of a wide variety of portfolios. Nevertheless, for other specific market anomaly-based portfolios, in particular those based on size and the price-to-cash flow ratio, revisions in expected consumption growth, determined according to the Rojo-Suárez et al. (2021) model, do not allow recursive preferences to outperform the classic Epstein and Zin (1991) model. This fact opens the door to additional proxies for revisions in expected consumption growth to capture investor expectations, as well as to other features not considered within the model setup, such as imperfect risk-sharing, heterogeneous beliefs across investors, or market microstructure characteristics, which may imply important effects on asset prices.

5. Conclusions

Following Epstein and Zin (1991) and Restoy and Weil (2011), revisions in expected consumption growth become a key element for the Epstein-Zin preferences to explain asset prices, as they allow to directly account for the effect of early resolution of uncertainty about future consumption paths. However, the fact that consumption growth still remains one of the most unpredictable macroeconomic series constitutes an important hurdle for the applicability of the model. On this basis, our results show that the unexpected shocks in consumption growth that result from the Rojo-Suárez et al. (2021) model exhibit significant predictive power for Japanese consumption growth and, consequently, help to improve the performance of the Epstein-Zin model in explaining the cross-sectional behavior of stock returns on the Tokyo Stock Exchange, for a wide range of market anomaly-based portfolios. Furthermore, our model allows us to explicitly relate stock returns and industry bubbles, consistent with the Campbell and Shiller (1988) return identity.

In order to examine the prevalence of our results, further research on the subject is mandatory. First, future research should address the extent to which consumption patterns and their pricing implications persist across countries and assets. In this context, we believe that our approach can be enriched by the contributions of research on the macroeconomic learning process, as developed by Pastor and Veronesi (2009) and Johannes et al. (2016). Furthermore, building on the competitive equilibrium defined by Suzuki (2016) for a pure exchange economy with multiple agents, our model can be easily adjusted to account for heterogeneous beliefs across countries in order to examine the effects of the cross-sectional variation of industry bubbles on global equity returns.

Second, future research should analyze the consistency between our results and the empirical specification of long-run models, such as those suggested by Bansal and Yaron (2004), Bansal et al. (2012), Roh et al. (2019) and Ruan (2021). For that purpose, the methodology suggested by Constantinides and Ghosh (2011) can help to overcome the problems that arise in estimating and testing long-run risk models. Finally, following Lee (2019), our model can be extended to consider smooth transition regimes in volatilities in order to account for time-varying features in expected stock returns. In our opinion, all these approaches can help to gain a further understanding on consumption dynamics and consequently improve the empirical performance of consumption-based asset pricing models.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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