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Cross-sectional implications of dynamic asset pricing with stochastic volatility and ambiguity aversion

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ABSTRACT

Building on recent research that highlights the importance of macroeconomic volatility and ambiguity aversion in explaining the dynamics of stock returns, in this paper we propose a dynamic asset pricing model that simultaneously accounts for stochastic macroeconomic volatility and ambiguity, assuming that investors deal with uncertainty about the mechanics of macroeconomic fluctuations using first-release consumption and revisions to aggregate consumption on vintage data. Our results show that the proposed model captures a large fraction of the cross-sectional variation of excess returns for a wide range of market anomaly portfolios. Furthermore, while the price of risk for ambiguity is positive and significant for the vast majority of assets under study, macroeconomic volatility yields ambiguous outcomes, although it significantly increases the explanatory power of the model for specific assets. Our results suggest that macroeconomic volatility and ambiguity complement each other in explaining the cross-sectional behavior of stock returns.

1. Introduction

Understanding how financial markets work and how economic agents price assets are classic questions in finance that are still the subject of lively debate in economic research. In this context, although the consumption-based asset pricing model (hereinafter, C-CAPM) provides a solid theoretical framework that allows asset prices to be directly related to macroeconomics, in practice its empirical performance has been traditionally poor (Hansen & Singleton, 1982; Weil, 1989). Consequently, recent research on asset pricing has provided us with different approaches aimed at overcoming some well-recognized problems tied to the C-CAPM framework. Thus, while some research suggests new common risk factors and explanatory variables that allow the model to better reproduce investor behavior (Boguth & Kuehn, 2013; Fama & French, 1993, 2015; Rojo-Suárez et al., 2020), other research proposes more complex utility functions that allow the pricing function to account for different non-separabilities (Campbell & Cochrane, 1999; Yogo, 2006; Zhang, 2020), long-run risks (Bansal & Yaron, 2004; Eraker, 2021; Kang et al., 2017; Liu & Matthies, 2022; Parker & Julliard, 2005; Pohl et al., 2021), or recursive preferences (Epstein & Zin, 1989; Restoy & Weil, 2011; Weil, 1989), among other features. However, most of these models assume the existence of a representative investor who not only knows the most updated data on macroeconomic aggregates, but is also aware of the mechanics of the underlying model that drives the economy, even though researchers do not have a good understanding of them (Lettau & Ludvigson, 2010).

In this paper we build on the theoretical basis proposed by Campbell et al. (2018) and Bansal et al. (2014), who study the

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implications of the stochastic nature of macroeconomic volatility on asset prices, as well as the contributions of Borup and Schütte (2021), who account for the fact that investors are not aware of the correct distribution of asset payoffs in what the literature calls *ambiguity*, to propose a four-factor asset pricing model that simultaneously accounts for stochastic macroeconomic volatility and ambiguity. In this regard, Mankiw et al. (1984) and Mankiw and Shapiro (1986) show that consumption corrections provide information about economic uncertainty, allowing the magnitude of the first revisions to consumption series on vintage data to capture uncertainty about the immediate consumption growth. On this basis, Borup and Schütte (2021) show that the difference between consumption forecasts and adjusted consumption is greater in times of uncertainty as consumption data require more severe corrections in times of great economic volatility. This fact raises questions about the relationship between macroeconomic volatility and ambiguity and, more specifically, about their joint effects in explaining the cross-sectional behavior of stock returns. Accordingly, in this paper we exploit the informativeness of the revisions to the first release consumption series to propose a dynamic asset pricing model that helps reconcile recent findings on stochastic volatility and ambiguity.

The contributions of this study are threefold. First, to the best of our knowledge, this is the first paper to explicitly combine the long-run risk model proposed by Bansal et al. (2014) (which the authors refer to as Macro-DCAPM-SV model) with the revised C-CAPM developed by Borup and Schütte (2021), to propose a multifactor asset pricing model that allows capturing the time-varying nature of the volatility of consumption growth, under the assumption that economic agents ignore the underlying model that drives the economy. Second, our study shows that both the volatility of consumption and ambiguity allow the model to capture a large fraction of the cross-sectional variation of stock returns, leading it to outperform the model proposed by Bansal et al. (2014), as well as other well-recognized asset pricing models. Third, the data series used to empirically evaluate the performance of the model comprise updated data that includes the period of economic turmoil due to the pandemic, characterized by a sharp drop in aggregate consumption and a significant increase in market volatility, thus contributing to enrich previous empirical research on macroeconomic volatility and ambiguity.

Regarding the theoretical background of the model, on the one hand we rely on the model proposed by Bansal et al. (2014), which build on Bansal and Yaron (2004) and Segal et al. (2015) to propose an intertemporal capital asset pricing model (hereinafter, i-CAPM) that captures the effects of macroeconomic volatility in long-run risk models by establishing three different sources of risk, namely cash flow risk, discount rate risk and volatility risk. Importantly, the authors conclude that models that ignore volatility risk may misspecify the stochastic discount factor (SDF) and equilibrium consumption, leading to strong distortions in model results. Furthermore, the authors show that, in the data, high volatility is usually accompanied by a sharp drop in realized and expected consumption and an increase in the risk premium, which is consistent with the dynamics predicted by the Bansal et al. (2014) model. Similarly, Campbell et al. (2018) develop an i-CAPM-based model that includes the stochastic volatility of consumption growth as an explanatory variable. The authors show that, under certain conditions, stock risk not only depends on betas with unexpected market returns and news about future returns, but also on betas with news about future market volatility.

On the other hand, we build on the findings of research on ambiguity, which argues that investors handle uncertainty about models differently from uncertainty about outcomes within a model. In this context, Borup and Schütte (2021) propose a revised C-CAPM that uses both consumption growth and ambiguity as model factors. In this regard, the authors conclude that while the initial releases on aggregate consumption are more suitable for asset pricing than the final revised releases, first revisions are strongly related to consumption growth ambiguity. Similarly, Lee et al. (2019) use the cross-sectional dispersion in real-time forecasts of real GDP growth as a measure for ambiguity to conclude that high ambiguity beta stocks provide lower future returns than low ambiguity beta stocks. Thimme and Völkert (2015) assume that investors behave according to the smooth ambiguity model of preference developed by Klibanoff et al. (2005, 2009) to evaluate the implications of ambiguity in the cross-section of expected returns. Remarkably, the authors find that ambiguity allows the model to price assets under plausible relative risk aversion coefficients, with risk aversion becoming negligible in explaining the cross-section of expected returns in the presence of ambiguity. Morimoto and Suzuki (2021) develop an asset pricing model for a multisector production economy, which includes ambiguity as a risk factor to explain the cross-sectional variation of stock returns. Likewise, Izhakian (2020) quantifies ambiguity using a Bayesian approach that allows the author to measure ambiguity by the volatility of probabilities.

Importantly, although a part of the literature estimates ambiguity using different indicators, such as the VIX index (Koh, 2017), the political uncertainty index (EPU) (Baker et al., 2016), or the financial uncertainty index (Jurado et al., 2015), in this paper we follow Borup and Schütte (2021) to use different versions of the consumption data series reported by the US Bureau of Economic Analysis (BEA) in the tables of the National Income and Product Accounts (NIPA), and in particular the first release consumption series. In this regard, it is worth mentioning that the BEA revises consumption data in order to provide timely estimates and correct for long-term trends and cyclical components in consumption data. Remarkably, Kroencke (2017) shows that the first release consumption series allows capturing short-run dynamics that are missing in the final consumption series due to the subsequent statistical procedures applied to the data. These benefits are similar to those provided by other consumption measures, such as electricity consumption (Da et al., 2016). Therefore, by assuming that the information set available for the representative investor includes the first release consumption rather than the revised consumption, we avoid the effects of irregular corrections on consumption data series. Furthermore, given the aforementioned evidence that the magnitude of the first revisions to consumption captures uncertainty about the immediate consumption growth, following Borup and Schütte (2021) we estimate ambiguity as a function of the difference between the first release consumption growth and the first revised consumption growth.

In order to evaluate the performance of our model, we follow Lewellen et al. (2010), Ferson et al. (2013) and Campbell (2018), who emphasize the convenience of using portfolios other than those sorted by size and the book-to-market equity ratio (hereinafter, BE/ME) in evaluating asset pricing models. Consequently, we use different anomaly portfolios comprising all stocks traded on the US equity market in the period from January 1980 to December 2021, namely, 25 size-operating profitability portfolios, 25 size-momentum portfolios, and 30 industry portfolios. Additionally, we evaluate the model on a set of 24 portfolios that simultaneously combine five market anomalies, comprising 6 size-BE/ME portfolios, 6 size-momentum portfolios, 6 size-long-term reversal portfolios, and 6 size-short-term reversal portfolios.

The remainder of the paper is organized as follows. Section 2 presents the theoretical model. Section 3 describes the data and provides the main summary statistics. Section 4 shows and discusses the results of the model. Section 5 concludes the paper.

2. Methodology

In this section we present the four-factor model proposed in the paper. For the sake of clarity, we first describe the main elements of the asset pricing model with stochastic volatility proposed by Bansal et al. (2014), to subsequently summarize the theoretical foundations of the revised C-CAPM with state-dependent ambiguity attitudes as defined by Borup and Schütte (2021). Finally, we derive the asset pricing model proposed in this paper, hereinafter referred to as the DCAPM-SVA model.

2.1. Consumption-based asset pricing with stochastic volatility

Assuming an endowment economy in which investor preferences follow a process of Kreps and Porteus (1978), Epstein and Zin (1989) define the following utility function:

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

where δ is the subjective discount factor, C_t represents the aggregate consumption, Ψ is the elasticity of intertemporal substitution (EIS) coefficient, and γ is the relative risk aversion (RRA) coefficient. Following Epstein and Zin (1989), the SDF can be represented as follows, with lowercase letters denoting logs:

$$m_{t+1} = \theta\log\delta - \frac{\theta}{\Psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1} \tag{2}$$

where $\theta = (1-\gamma)/(1-1/\Psi)$, Δc_{t+1} is the log consumption growth, and $r_{c,t+1}$ is the logarithmic return on the wealth portfolio —i.e. the consumption asset— at time $t+1$. Assuming that the SDF and the return on the wealth portfolio are jointly log-normal, we obtain the following Euler equation:

$$E_t\Delta c_{t+1} = \Psi log\delta + \Psi E_t r_{c,t+1} - \frac{\Psi-1}{\gamma-1}V_t \tag{3}$$

where V_t denotes the conditional variance of the SDF plus the return on the wealth portfolio, following:

$$V_t = \frac{1}{2}\sigma_t^2\left(m_{t+1}+r_{c,t+1}\right) = \frac{1}{2}\sigma_t^2(m_{t+1}) + \text{cov}_t\left(m_{t+1}, r_{c,t+1}\right) + \frac{1}{2}\sigma_t^2\left(r_{c,t+1}\right) \tag{4}$$

As shown in Equation (3), when V_t is a constant or the EIS coefficient is equal to one, the volatility shocks are not reflected separately in the expected consumption growth. In this regard, although a part of the related research assumes constant volatility over time (Campbell, 1996; Campbell & Vuolteenaho, 2004; Lustig & Van Nieuwerburgh, 2008), we follow Bansal et al. (2014) to consider stochastic volatility. Thus, denoting W_t as the wealth at time t, the classic budget constraint follows:

$$W_{t+1} = (W_t - C_t)R_{c,t+1} \tag{5}$$

Using logs to linearize Equation (5), the budget constraint can be rewritten as follows:

$$r_{c,t+1} = \tau_0 + \omega c_{t+1} - \frac{1}{\tau_1}\omega c_t + \Delta c_{t+1} \tag{6}$$

where $\omega c_t = \log(W_t/C_t)$, and τ_0 and τ_1 are parameters. Operating recursively forward, we can write the unexpected consumption as a function of the revisions in the future return on the wealth portfolio minus the revisions in the expected cash flow from the consumption asset:

$$c_{t+1} - E_t c_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\tau_1^j r_{c,t+j+1} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\tau_1^j\Delta c_{t+j+1} \tag{7}$$

Using the notation $N_{x,t+1}$ to indicate revisions (i.e. news) to the expected value of x, Equation (7) can be rewritten as follows:

$$N_{C,t+1} = N_{R,t+1} + N_{DR,t+1} + N_{CF,t+1} \tag{8}$$

where the term on the left-hand side of Equation (8) is the term on the left-hand side of Equation (7), and the last term on the right-hand side of Equation (8) is the last term on the right-hand side of Equation (7). The term $N_{R,t+1} + N_{DR,t+1}$ in Equation (8) represents the first term on the right-hand side of Equation (7), where:

$$N_{R,t+1} \equiv r_{c,t+1} - E_t r_{c,t+1}$$

$$N_{DR,t+1} \equiv (E_{t+1} - E_t)\sum_{j=1}^{\infty} \tau_1^j r_{c,t+j+1} \tag{9}$$

Using Equation (3), we can express Equation (8) as follows:

$$N_{C,t+1} = N_{R,t+1} + (1-\Psi)N_{DR,t+1} + \frac{\Psi - 1}{\gamma - 1} N_{V,t+1} \tag{10}$$

where

$$N_{V,t+1} \equiv (E_{t+1} - E_t)\sum_{j=1}^{\infty} \tau_1^j V_{t+j} \tag{11}$$

Equations (2) and (10) allow us to write the innovation to the SDF as a function of innovations in Equations (9) and (11):

$$m_{t+1} - E_t m_{t+1} = -\gamma N_{CF,t+1} + N_{DR,t+1} + N_{V,t+1} \tag{12}$$

Considering that the excess return of a stock —i.e. the return of a long position in a stock and a short position in the risk-free rate— can be written as the negative covariance between the asset's return and the SDF, Equation (12) allows us to write the log excess return as follows:

$$E_t r_{i,t+1} - r_{f,t} + \frac{1}{2}\sigma_t^2 r_{i,t+1} = \gamma \mathrm{cov}_t\left(r_{i,t+1}, N_{CF,t+1}\right) - \mathrm{cov}_t\left(r_{i,t+1}, N_{DR,t+1}\right) - \mathrm{cov}_t\left(r_{i,t+1}, N_{V,t+1}\right) \tag{13}$$

Denoting the excess return of a stock i by $r_{i,t+1}^e$ and assuming unconditional expectations, variances and covariances, Equation (13) can be easily transformed into the following beta model:

$$Er_{i,t+1}^e = \lambda^{CF}\beta_i^{CF} + \lambda^{DR}\beta_i^{DR} + \lambda^V \beta_i^V \tag{14}$$

where lambda coefficients denote the prices of risk, specifically, cash flow risk (λ^{CF}), discount rate risk (λ^{DR}) and economic volatility risk (λ^V), and beta coefficients represent the risk exposures (i.e. the slope coefficients) that result from the time series regression of excess returns on model factors.

2.2. Ambiguity

Following Borup and Schütte (2021), the logarithmic growth rate of nondurable consumption for the period from $t-1$ to t and released at time $t+k$ —hereinafter denoted as $\Delta c_{t,t+k}$— can be written as a function of the growth rate of the first release consumption $\Delta c_{t,t}$ and the subsequent revisions $a_{t,t+k}$:

$$\Delta c_{t,t+k} = \Delta c_{t,t} + a_{t,t+k} \tag{15}$$

Using Equation (15), Borup and Schütte (2021) propose the following linear SDF, which assumes that attitudes towards ambiguity are state dependent:

$$m_{t+1} = 1 - \alpha_0 \Delta c_{t+1,t+1} - \alpha_1 \Delta c_{t+1,t+1} \cdot \left|a_{t+1,t+1+k}\right| \tag{16}$$

where α_0 and α_1 are parameters. At this point, it should be noted that, although previous experimental studies underline the complexity of developing a unique theoretical model that captures ambiguity preferences (Halevy, 2007; Abdellaoui et al., 2011), Borup and Schütte (2021) build on recent experimental research in economics that provide strong evidence that attitudes towards ambiguity are state dependent (Du and Budescu, 2005; Chakravarty and Roy, 2009; Brenner and Izhakian, 2018). In particular, while Halevy (2007) shows that different groups of subjects exhibiting a neutral, averse or ambiguity-seeking behavior require alternative theoretical models to account for attitudes to ambiguity, Abdellaoui et al. (2011) find that attitudes towards ambiguity depend not only on the subject but also on the source of uncertainty. In this regard, Du and Budescu (2005) find that investor decisions can be systematically influenced by the context of the task and the perceived gains or losses. Similarly, Chakravarty and Roy (2009) use a recursive expected utility model to show that subjects are ambiguity-neutral over gains and ambiguity-seeking over losses. Furthermore, in the specific field of asset pricing, Brenner and Izhakian (2018) show that the level of investors' aversion or willingness to ambiguity depends on the expected probability of favorable returns.

Therefore, as noted by Borup and Schütte (2021), these results are consistent with investors exhibiting ambiguity aversion for positive states (i.e. high probability of gains) and ambiguity seeking for negative states (high probability of losses). In this context, as shown in Equation (16), Borup and Schütte (2021) include an additional term in the classic consumption SDF to capture the state-dependent nature of attitudes towards ambiguity. Specifically, while the second term on the right-hand side of Equation (16) captures the classic risk exposure to consumption growth (determined using the first release consumption), the third term measures the effects of revisions to consumption growth on the SDF when first release consumption growth is higher or lower, thus capturing state-dependent attitudes towards ambiguity under the Borup and Schütte (2021) setup. Thus, Equation (16) allows Borup and Schütte

(2021) to derive their revised C-CAPM:

$$E_t r^e_{i,t+1} = \lambda^{CF^*} \beta_i^{CF^*} + \lambda^A \beta_i^A \tag{17}$$

where $\beta_i^{CF^*}$ and β^A are the slope coefficients of the time series regression of excess returns on $\Delta c_{t+1,t+1}$ and $\Delta c_{t+1,t+1} \cdot |a_{t+1,t+1+k}|$, respectively, and λ^{CF^*} and λ^A are the prices of risk. Hence, the approach proposed by Borup and Schütte (2021) allows the model to directly relate the SDF —and consequently the pricing function— to macroeconomic data in a tractable way, which is a desirable property for the purpose of our study, shared with other methodologies developed in the area (see Brenner and Izhakian (2018) and Lee et al. (2019)). Other approaches such as those stemming from life-cycle consumption-based asset pricing (see Klibanoff et al. (2005, 2009) and Thimme and Völkert (2015)) can also be adjusted to account for stochastic macroeconomic volatility, but at the cost of significantly increasing the complexity of the model.

2.3. The DCAPM-SVA model

Based on the fact that the term $N_{CF,t+1}$ in Equation (12) represents innovations in expected cash flows from the consumption asset, that is, innovations in consumption growth, we build on Equation (12) to assume that the information set available for investors includes the first release consumption instead of the revised consumption. Additionally, we assume state-dependent ambiguity attitudes, as captured by the third term on the right-hand side of Equation (16). These assumptions allow us to rewrite Equation (12) as follows:

$$m_{t+1} - E_t m_{t+1} = -\gamma N_{CF^*,t+1} + N_{DR,t+1} + N_{V,t+1} + N_{A,t+1} \tag{18}$$

where $N_{A,t+1}$ represents innovations in the expected revisions of consumption growth. Equation (18) allows us to write the excess return of a stock i as follows:

$$E r^e_{i,t+1} = \gamma \operatorname{cov}_t\left(r_{i,t+1}, N_{CF^*,t+1}\right) - \operatorname{cov}_t\left(r_{i,t+1}, N_{DR,t+1}\right) - \operatorname{cov}_t\left(r_{i,t+1}, N_{V,t+1}\right) + \alpha_1 \operatorname{cov}_t\left(r_{i,t+1}, N_{A,t+1}\right) \tag{19}$$

or equivalently:

$$E r^e_{i,t+1} = \lambda^{CF^*} \beta_i^{CF^*} + \lambda^{DR} \beta_i^{DR} + \lambda^V \beta_i^V + \lambda^A \beta_i^A \tag{20}$$

Hence, ambiguity leads the pricing function derived by Bansal et al. (2014) to include a fourth risk factor, in what we call the DCAPM-SVA model. In the next section we study the extent to which the model allows explaining the cross-sectional behavior of stock returns.

3. Data

In order to evaluate the performance of the model, we compile monthly return data and macroeconomic data series from the Kenneth R. French website and the economic database of the Federal Reserve Bank of St. Louis (FRED), respectively. In this regard, it should be noted that the fact that the Archival Federal Reserve Economic Database (ALFRED) at the FRED reports monthly consumption revisions on vintage NIPA data from December 1979 constraints our sample size to the period from January 1980 to December 2021. Regarding market data, we use four sets of market anomaly portfolios that comprise all stocks traded on the US equity market in the period under study. Following Lewellen et al. (2010), the first set of portfolios combines a wide range of market anomalies into four double-sort portfolios, namely, 6 portfolios sorted by size and BE/ME, 6 portfolios sorted by size and momentum, 6 portfolios sorted by size and long-term reversal, and 6 portfolios sorted by size and short-term reversal. Hereinafter, we refer to this set of portfolios as the set of 'composite portfolios'. The other sets of anomaly portfolios comprise 25 portfolios sorted by size and operating profitability, 25 portfolios sorted by size and momentum, and 30 industry portfolios.

As noted, we compile consumption data on non-nondurable goods from the ALFRED database. We use the growth rate of the first release consumption to proxy for consumption growth in the DCAPM-SVA model and to estimate the aggregate economic volatility. Although Bansal et al. (2014) use the sum of squares of monthly industrial production growth to estimate the aggregate economic volatility, we instead use the variance of the 12-month rolling window of the first release consumption growth, according to the following expression:

$$\widehat{V}_t = \sum_{j=1}^{12} \frac{\left(\Delta c_{t+j-12,t+j-12} - \Delta \bar{c}_{t,t}\right)^2}{11} \tag{21}$$

where $\Delta \bar{c}_{t,t}$ represents the average annual first release consumption. In any case, it should be noted that Bansal et al. (2014) check that their results do not materially change by using annual consumption growth instead of industrial production growth. We use the same approach to estimate the aggregate economic volatility required by the Bansal et al. (2014) model, but replacing first release consumption growth with final consumption growth, consistent with the methodology used by the authors. On the other hand, following Borup and Schütte (2021), we use Equation (16) to estimate the ambiguity factor assuming $k = 1$, as follows:

Table 1
Summary statistics.

Panel A: 24 composite portfolios

	Low Means	2	High		Low St. Dev.	2	High
Small-BE/ME	0.32	0.76	0.78	Small-BE/ME	6.80	5.36	5.64
Big-BE/ME	0.62	0.54	0.61	Big-BE/ME	4.63	4.45	5.22
Small-Mom	0.12	0.71	0.94	Small-Mom	7.32	5.20	6.11
Big-Mom	0.38	0.56	0.69	Big-Mom	6.15	4.30	4.73
Small-LT rev	0.71	0.78	0.60	Small-LT rev	6.56	5.05	5.77
Big-LT rev	0.65	0.62	0.59	Big-LT rev	5.11	4.15	4.83
Small-ST rev	0.64	0.72	0.33	Small-ST rev	7.23	5.42	5.99
Big-ST rev	0.61	0.67	0.42	Big-ST rev	5.85	4.34	4.63

Panel B: 25 size-operating profitability portfolios

Op. prof.	Low Means	2	3	4	High	Op. prof.	Low St. Dev.	2	3	4	High
Small	0.17	0.73	0.72	0.67	0.53	Small	7.24	5.46	5.31	5.68	6.66
2	0.26	0.57	0.74	0.77	0.78	2	7.13	5.65	5.26	5.60	6.31
3	0.35	0.63	0.71	0.76	0.78	3	6.94	5.26	5.03	5.31	5.79
4	0.49	0.65	0.69	0.76	0.75	4	6.37	5.21	4.82	5.02	5.21
Big	0.29	0.53	0.49	0.61	0.66	Big	5.94	4.78	4.62	4.31	4.36

Panel C: 25 size-momentum portfolios

Momentum	Low Means	2	3	4	High	Momentum	Low St. Dev.	2	3	4	High
Small	−0.25	0.48	0.72	0.88	1.02	Small	8.21	5.69	5.20	5.26	6.49
2	0.01	0.60	0.75	0.88	0.95	2	8.18	5.96	5.29	5.31	6.72
3	0.20	0.56	0.72	0.69	0.87	3	7.82	5.73	5.09	5.05	6.29
4	0.07	0.62	0.74	0.73	0.81	4	8.12	5.70	4.88	4.64	5.78
Big	0.22	0.59	0.51	0.60	0.68	Big	7.34	4.98	4.38	4.22	5.10

Panel D: 30 industry portfolios

Means						St. Dev.					
Food	Beer	Smoke	Games	Books	Hshld	Food	Beer	Smoke	Games	Books	Hshld
0.77	0.87	0.86	0.70	0.39	0.61	4.16	4.87	6.54	7.04	5.90	4.41
Clths	Hlth	Chems	Txtls	Cnstr	Steel	Clths	Hlth	Chems	Txtls	Cnstr	Steel
0.70	0.73	0.54	0.42	0.48	0.39	6.44	4.61	5.83	7.98	6.39	8.19
FabPr	ElcEq	Autos	Carry	Mines	Coal	FabPr	ElcEq	Autos	Carry	Mines	Coal
0.46	0.71	0.58	0.60	0.05	−0.38	6.63	6.53	7.86	6.52	8.16	11.46
Oil	Util	Telcm	Servs	BusEq	Paper	Oil	Util	Telcm	Servs	BusEq	Paper
0.26	0.54	0.59	0.71	0.55	0.51	6.17	3.89	4.99	6.34	7.26	5.16
Trans	Whlsl	Rtail	Meals	Fin	Other	Trans	Whlsl	Rtail	Meals	Fin	Other
0.56	0.48	0.84	0.72	0.60	0.20	5.58	5.21	5.37	5.23	5.60	5.72

Panel E: Market factors and macroeconomic variables

	RMRF	SMB	HML	RMW	CMA		$\Delta C_{t,t}$	$\Delta C_{t,t+k}$		$\widehat{V}_t$	Ambiguity
Means	0.57	0.05	0.16	0.29	0.25	Means	0.31	0.35	Means	0.03	−0.01
St. Dev.	4.54	2.89	2.98	2.39	1.94	St. Dev.	1.72	1.19	St. Dev.	0.08	0.28

Notes: The table shows the means and standard deviations of the excess returns provided by different sets of anomaly portfolios comprising all stocks traded on the US equity market, for the period from January 1980 to December 2021, specifically: (i) a first set that combines four different double-sort portfolios, namely, 6 size-BE/ME portfolios, 6 size-momentum portfolios, 6 size-long-term reversal portfolios, and 6 size-short-term reversal portfolios, in what we call the set of 'composite portfolios', (ii) 25 size-operating profitability portfolios, (iii) 25 size-momentum portfolios, and (iv) 30 industry portfolios. Additionally, Panel E shows the mean returns and standards deviations of the market factors in the Fama-French five-factor model, namely, RMRF (the return of the value-weighted market portfolio minus the risk-free rate), SMB (the small minus big market value factor), HML (the high minus low book-to-market equity factor), RMW (the excess return of the most profitable stocks minus the least profitable), and CMA (the excess return of companies that invest conservatively minus aggressively). We compile all return data from the Kenneth R. French website. Consumption growth $\Delta C_{t,t}$ in Panel E denotes the growth rate of the first release consumption, while $\Delta C_{t,t+k}$ denotes the growth rate of the final consumption. The term $\widehat{V}_t$ denotes the variance of the 12-month rolling window of the first release consumption growth, and 'Ambiguity' represents the ambiguity factor, determined following Borup and Schütte (2021). All results are determined on a monthly basis. Means and standard deviations are percentages.

$$f_t^A = \Delta c_{t,t} \cdot |a_{t,t+1}| \tag{22}$$

For comparative purposes, in the next section we study the results provided by the DCAPM-SVA model under these specifications, but also those delivered by the Bansal et al. (2014) model, the classic C-CAPM, the CAPM, and the Fama-French three- and five-factor models (Fama & French, 1993, 2015). We compile all data series for the required market factors from the Kenneth R. French website.

Table 2
Correlations.

Panel A: 24 composite portfolios

	Low	2	High		Low	2	High
	Correlations with $\Delta C_{t,t}$				Correlations with $\Delta C_{t,t+k}$		
Small-BE/ME	18.31	19.41	22.13	Small-BE/ME	22.51	24.84	27.93
Big-BE/ME	13.65	14.47	20.50	Big-BE/ME	19.15	22.67	28.15
Small-Mom	15.52	20.04	20.79	Small-Mom	24.95	26.07	24.43
Big-Mom	13.90	13.62	15.12	Big-Mom	26.70	20.79	20.15
Small-LT rev	20.76	20.80	16.76	Small-LT rev	27.54	24.92	23.42
Big-LT rev	16.91	14.22	14.57	Big-LT rev	22.29	20.20	21.41
Small-ST rev	21.60	19.90	16.52	Small-ST rev	27.09	27.04	23.23
Big-ST rev	21.20	15.98	10.87	Big-ST rev	28.52	22.84	18.71
	Correlations with $\widehat{V}_t$				Correlations with ambiguity		
Small-BE/ME	11.89	10.14	12.38	Small-BE/ME	−0.07	0.59	1.46
Big-BE/ME	10.82	9.55	8.45	Big-BE/ME	−1.94	−3.33	−1.95
Small-Mom	16.00	10.89	9.63	Small-Mom	−5.55	0.24	2.11
Big-Mom	9.29	11.53	10.95	Big-Mom	−6.84	−3.17	−0.55
Small-LT rev	13.26	10.47	11.34	Small-LT rev	−0.29	1.95	−1.89
Big-LT rev	10.63	10.58	9.48	Big-LT rev	−0.54	−2.16	−2.77
Small-ST rev	11.54	12.78	12.36	Small-ST rev	0.39	−0.67	−2.43
Big-ST rev	8.95	10.14	12.42	Big-ST rev	−0.95	−1.96	−5.06

Panel B: 25 size-operating profitability portfolios

Op. prof.	Low	2	3	4	High	Op. prof.	Low	2	3	4	High
	Correlations with $\Delta C_{t,t}$						Correlations with $\Delta C_{t,t+k}$				
Small	17.40	19.29	18.71	21.32	23.41	Small	22.52	23.36	24.67	27.19	27.82
2	16.01	19.24	19.04	19.80	24.44	2	21.88	24.62	23.38	25.89	29.90
3	17.72	19.43	21.87	21.28	22.79	3	19.99	24.90	27.40	26.96	28.85
4	18.78	21.70	19.74	18.23	17.52	4	23.94	27.21	28.79	24.86	23.44
Big	12.79	17.85	15.22	11.65	12.87	Big	21.79	24.64	21.07	18.23	18.99
	Correlations with $\widehat{V}_t$						Correlations with ambiguity				
Small	12.99	10.01	9.77	11.89	14.31	Small	−2.27	1.37	1.06	0.76	1.19
2	10.92	9.08	9.57	11.59	11.55	2	−1.38	0.74	2.45	1.31	1.22
3	12.05	10.79	9.15	12.64	11.76	3	1.46	0.48	2.72	1.13	1.18
4	13.44	9.52	9.82	12.99	12.18	4	−1.44	1.25	−1.18	−0.35	−0.78
Big	8.94	12.02	10.54	9.26	10.22	Big	−6.60	−1.62	−2.12	−3.52	−2.38

Panel C: 25 size-momentum portfolios

Momentum	Low	2	3	4	High	Momentum	Low	2	3	4	High
	Correlations with $\Delta C_{t,t}$						Correlations with $\Delta C_{t,t+k}$				
Small	15.49	18.44	18.89	16.94	17.73	Small	25.75	26.38	25.71	24.54	24.16
2	13.94	19.17	18.21	21.56	21.44	2	23.66	26.11	24.29	25.95	25.26
3	13.29	19.35	20.36	21.01	20.46	3	22.55	28.14	26.08	26.26	24.30
4	16.98	16.81	18.80	17.97	21.27	4	30.18	26.32	25.54	22.23	25.28
Big	16.55	10.98	10.81	12.79	14.54	Big	30.18	21.86	19.12	18.49	18.92
	Correlations with $\widehat{V}_t$						Correlations with ambiguity				
Small	17.53	13.64	10.57	10.73	10.65	Small	−7.53	−3.37	−2.17	−3.32	−2.28
2	16.38	11.14	9.67	10.71	8.85	2	−5.90	−0.30	−0.32	2.58	3.25
3	15.01	12.80	11.17	10.59	8.99	3	−6.10	−2.75	0.75	2.33	2.83
4	12.61	12.49	11.65	9.55	10.74	4	−7.33	−4.42	−1.46	1.60	2.90
Big	7.11	9.45	11.96	11.24	9.48	Big	−6.79	−6.81	−6.11	−1.25	0.24

Panel D: 30 industry portfolios

Correlations with $\Delta C_{t,t}$						Correlations with $\Delta C_{t,t+k}$					
Food	Beer	Smoke	Games	Books	Hshld	Food	Beer	Smoke	Games	Books	Hshld
8.39	3.79	2.02	14.99	19.42	6.89	11.83	11.96	11.34	20.85	23.99	9.66
Clths	Hlth	Chems	Txtls	Cnstr	Steel	Clths	Hlth	Chems	Txtls	Cnstr	Steel
12.18	9.03	16.87	23.11	21.89	15.78	15.46	14.57	23.58	26.06	27.25	26.31
FabPr	ElcEq	Autos	Carry	Mines	Coal	FabPr	ElcEq	Autos	Carry	Mines	Coal
16.46	19.40	20.24	17.49	10.67	17.07	22.80	21.61	24.52	23.46	23.13	32.60
Oil	Util	Telcm	Servs	BusEq	Paper	Oil	Util	Telcm	Servs	BusEq	Paper
24.04	9.94	12.97	14.28	12.27	9.52	38.05	16.02	15.21	16.05	18.09	12.90
Trans	Whlsl	Rtail	Meals	Fin	Other	Trans	Whlsl	Rtail	Meals	Fin	Other
10.85	17.43	11.17	13.89	12.07	7.58	12.73	23.38	6.85	21.55	19.20	11.03
Correlations with $\widehat{V}_t$						Correlations with ambiguity					
Food	Beer	Smoke	Games	Books	Hshld	Food	Beer	Smoke	Games	Books	Hshld
6.28	5.88	3.41	12.48	11.54	10.08	−2.85	−6.54	−5.33	−1.83	2.16	−2.62
Clths	Hlth	Chems	Txtls	Cnstr	Steel	Clths	Hlth	Chems	Txtls	Cnstr	Steel
11.47	7.45	11.56	8.47	8.70	8.02	−0.04	−4.02	−2.47	7.18	4.50	−3.08

(*continued on next page*)

Table 2 (*continued*)

FabPr	ElcEq	Autos	Carry	Mines	Coal	FabPr	ElcEq	Autos	Carry	Mines	Coal
11.55	11.42	18.70	7.33	11.60	7.39	−0.57	3.84	5.24	−3.14	−7.70	−9.79
Oil	Util	Telcm	Servs	BusEq	Paper	Oil	Util	Telcm	Servs	BusEq	Paper
3.28	4.59	8.37	8.28	10.02	11.17	−3.37	−3.18	0.80	−0.08	0.39	−1.17
Trans	Whlsl	Rtail	Meals	Fin	Other	Trans	Whlsl	Rtail	Meals	Fin	Other
11.86	11.44	8.48	9.36	7.95	8.44	0.13	−1.37	4.51	−1.92	−4.88	−3.76

Notes: The table shows the correlations between different macroeconomic variables and the excess returns provided by four sets of anomaly portfolios comprising all stocks traded on the US equity market, for the period from January 1980 to December 2021, specifically: (i) a first set that combines four different double-sort portfolios, namely, 6 size-BE/ME portfolios, 6 size-momentum portfolios, 6 size-long-term reversal portfolios, and 6 size-short-term reversal portfolios, in what we call the set of 'composite portfolios', (ii) 25 size-operating profitability portfolios, (iii) 25 size-momentum portfolios, and (iv) 30 industry portfolios. We compile all return data from the Kenneth R. French website. Consumption growth $\Delta C_{t,t}$ denotes the growth rate of the first release consumption, while $\Delta C_{t,t+k}$ denotes the growth rate of the final consumption. The term $\widehat{V}_t$ denotes the variance of the 12-month rolling window of the first release consumption growth, and 'Ambiguity' represents the ambiguity factor, determined following Borup and Schütte (2021). All results are determined using monthly data.

Additionally, we use the excess return of the value-weighted market portfolio (hereinafter referred to as RMRF), as provided by Kenneth R. French, to proxy for the return on the wealth portfolio in both the DCAPM-SVA model and the Bansal et al. (2014) model.

Table 1 shows the main summary statistics for test assets, market factors and macroeconomic variables, while Table 2 shows the correlations between macroeconomic variables and the excess returns provided by our four sets of anomaly portfolios. The results in Table 1, Panel E, show that, with a standard deviation of 1.72%, the first release consumption growth is more volatile than its revised counterpart, which delivers a standard deviation of 1.19%. In any case, Table 2 shows that, in general, the revised consumption growth is more correlated with excess returns than the first release consumption growth. Additionally, it is worth noting that while in most of cases consumption growth (both first released and revised) and macroeconomic volatility $\widehat{V}_t$ are positively correlated with excess returns, the opposite is true for ambiguity. However, it is important to note that the correlations in Table 2 do not condition the performance of the models under study, but rather the correlation between the expected returns and the covariances between factors

Table 3
Macro VAR estimates.

Panel A: DCAPM-SVA model						
	$\Delta C_{t,t}$	$RMRF_t$	PD_t	$\widehat{V}_t$	f_t^A	R^2
$\Delta C_{t+1,t+1}$	−0.22	0.01	0.00	1.35	0.67	0.03
	(-3.67)	(0.85)	(1.06)	(1.48)	(2.01)	
$RMRF_{t+1}$	−0.13	0.07	0.00	4.98	0.35	0.02
	(-0.85)	(1.45)	(-1.11)	(2.08)	(0.41)	
PD_{t+1}	−7.61	19.18	0.99	294.63	26.73	0.99
	(-1.42)	(12.18)	(241.30)	(3.59)	(0.89)	
$\widehat{V}_{t+1}$	0.00	0.00	0.00	0.93	0.01	0.87
	(-1.67)	(0.46)	(-0.90)	(54.82)	(0.83)	
f_{t+1}^A	0.00	−0.01	0.00	0.03	−0.02	0.01
	(-0.36)	(-1.87)	(0.03)	(0.16)	(-0.40)	
Panel B: Bansal et al. (2014) model						
	$\Delta C_{t,t+k}$	$RMRF_t$	PD_t	$\widehat{V}_t$		R^2
$\Delta C_{t+1,t+1+k}$	−0.30	0.05	0.00	5.73		0.13
	(-6.86)	(3.91)	(-0.41)	(4.52)		
$RMRF_{t+1}$	−0.14	0.07	0.00	13.09		0.02
	(-0.83)	(1.48)	(-1.51)	(2.69)		
PD_{t+1}	−9.34	19.42	0.99	649.97		0.99
	(-1.63)	(12.38)	(238.57)	(3.90)		
$\widehat{V}_{t+1}$	0.00	0.00	0.00	0.96		0.91
	(-4.34)	(-0.77)	(-0.01)	(69.14)		

Notes: The table shows the coefficients estimates, *t*-statistics (in parentheses), and R^2 statistics of the forecasting regressions within the Macro VAR specification used to estimate innovations in the DCAPM-SVA model (Panel A) and the Bansal et al. (2014) model (Panel B). For the DCAPM-SVA model, we define a vector of state variables that include the first release consumption growth ($\Delta C_{t,t}$), the return of the value-weighted market portfolio minus the risk-free rate ($RMRF_t$), the market price-dividend ratio (PD_t), the aggregate economic volatility estimated by the variance of the 12-month rolling window of the first release consumption growth ($\widehat{V}_t$), and the ambiguity factor determined following the Borup and Schütte (2021) methodology (f_t^A). For the Bansal et al. (2014) model we use the same state variables, with the following differences: (i) we use final consumption growth ($\Delta C_{t,t+k}$) instead of first release consumption growth, (ii) the aggregate macroeconomic volatility is determined based on final consumption growth instead of first release consumption growth, and (iii) we ignore the ambiguity factor. We use OLS on monthly data series to estimate all regressions.

Table 4
Regression results.

Row	Model	Intercept	Macroeconomic factors λ^{CF}	λ^{V}	λ^{A}	Fama-French factors λ^{RMRF}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	R^2	MAE (%)	*J*-test
Panel A: 24 composite portfolios													
1	DCAPM-SVA	0.011	0.014	0.000	0.003	-0.006					0.785	0.06	41.422
		(2.206)	(2.587)	(-1.148)	(2.169)	(-1.009)					0.352		(0.002)
2	Bansal et al. (2014) model	0.010	0.002	0.000		-0.004					0.312	0.12	78.325
		(2.680)	(0.596)	(-1.270)		(-0.959)					0.227		(0.000)
3	C-CAPM	0.007	-0.001								0.013	0.13	101.911
		(3.367)	(-0.333)								0.004		(0.000)
4	CAPM	0.010				-0.004					0.112	0.13	98.366
		(3.073)				(-0.992)					0.103		(0.000)
5	Fama-French (3 factors)	0.014				-0.009	0.001	0.001			0.275	0.11	93.509
		(4.230)				(-2.177)	(0.549)	(0.994)			0.231		(0.000)
6	Fama-French (5 factors)	0.000				0.005	0.001	0.001	0.009	0.002	0.514	0.09	61.367
		(0.049)				(0.806)	(0.881)	(0.563)	(3.642)	(1.401)	0.392		(0.000)
Panel B: 25 size-operating profitability portfolios													
7	DCAPM-SVA	0.015	0.010	0.000	0.002	-0.010					0.727	0.08	19.446
		(3.371)	(1.863)	(-0.937)	(2.003)	(-1.919)					0.644		(0.493)
8	Bansal et al. (2014) model	0.017	0.004	0.000		-0.011					0.649	0.08	31.012
		(4.394)	(1.536)	(0.742)		(-2.529)					0.481		(0.073)
9	C-CAPM	0.007	-0.001								0.006	0.14	45.574
		(3.185)	(-0.287)								0.006		(0.003)
10	CAPM	0.016				-0.009					0.404	0.10	39.168
		(4.440)				(2.131)					0.385		(0.019)
11	Fama-French (3 factors)	0.010				-0.005	-0.001	0.005			0.603	0.09	38.756
		(3.560)				(1.267)	(-0.478)	(2.399)			0.441		(0.010)
12	Fama-French (5 factors)	0.008				-0.002	-0.001	0.001	0.003	0.001	0.796	0.06	31.851
		(2.397)				(-0.506)	(-0.450)	(0.764)	(3.011)	(0.272)	0.761		(0.032)
Panel C: 25 size-momentum portfolios													
13	DCAPM-SVA	0.011	0.011	-0.001	0.002	-0.004					0.816	0.09	30.807
		(2.813)	(1.813)	(-1.677)	(2.074)	(-0.940)					0.612		(0.058)
14	Bansal et al. (2014) model	0.012	-0.004	0.000		-0.004					0.493	0.17	48.833
		(2.746)	(-1.165)	(-1.830)		(-0.880)					0.430		(0.001)
15	C-CAPM	0.013	-0.005								0.358	0.19	72.559
		(5.480)	(-2.421)								0.197		(0.000)
16	CAPM	0.018				-0.011					0.432	0.17	80.200
		(5.637)				(-2.829)					0.366		(0.000)

(*continued on next page*)

Table 4 (*continued*)

Row	Model	Intercept	Macroeconomic factors λ^{CF}	λ^{V}	λ^{A}	Fama-French factors λ^{RMRF}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	R^2	MAE (%)	*J*-test
17	Fama-French (3 factors)	0.021				-0.013	0.000	-0.004			0.686	0.13	70.943
		(5.273)				(-3.202)	(0.303)	(-1.430)			0.549		(0.000)
18	Fama-French (5 factors)	0.013				-0.007	0.002	-0.006	0.007	-0.003	0.771	0.11	61.314
		(3.312)				(-1.616)	(1.094)	(-1.825)	(2.693)	(-0.962)	0.717		(0.000)
Panel D: 30 industry portfolios													
19	DCAPM-SVA	0.009	0.000	0.000	0.001	-0.003					0.665	0.13	26.369
		(3.351)	(0.084)	(-0.497)	(1.243)	(-1.008)					0.343		(0.388)
20	Bansal et al. (2014) model	0.008	-0.004	0.000		-0.002					0.600	0.14	26.874
		(3.264)	(-2.233)	(0.425)		(-0.664)					0.284		(0.416)
21	C-CAPM	0.009	-0.003								0.584	0.14	28.269
		(4.185)	(-2.308)								0.286		(0.450)
22	CAPM	0.009				-0.004					0.123	0.18	31.320
		(3.741)				(-1.200)					0.029		(0.303)
23	Fama-French (3 factors)	0.003				0.003	-0.008	-0.002			0.469	0.14	23.573
		(1.025)				(0.890)	(-2.493)	(0.961)			0.398		(0.600)
24	Fama-French (5 factors)	0.002				0.004	-0.008	-0.004	0.007	-0.005	0.719	0.10	17.160
		(0.537)				(1.045)	(2.380)	(-1.843)	(2.466)	(-1.940)	0.658		(0.842)

Notes: We evaluate the models under analysis on four sets of anomaly portfolios comprising all stocks traded on the US equity market, for the period from January 1980 to December 2021, specifically: (i) a first set that combines four different double-sort portfolios, namely, 6 size-BE/ME portfolios, 6 size-momentum portfolios, 6 size-long-term reversal portfolios, and 6 size-short-term reversal portfolios, in what we call the set of 'composite portfolios', (ii) 25 size-operating profitability portfolios, (iii) 25 size-momentum portfolios, and (iv) 30 industry portfolios. We compile all return data from the Kenneth R. French website. To estimate the models, we map the two-pass cross-sectional regression procedure into GMM, 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 column labeled 'R^2' shows the OLS and 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 monthly basis.

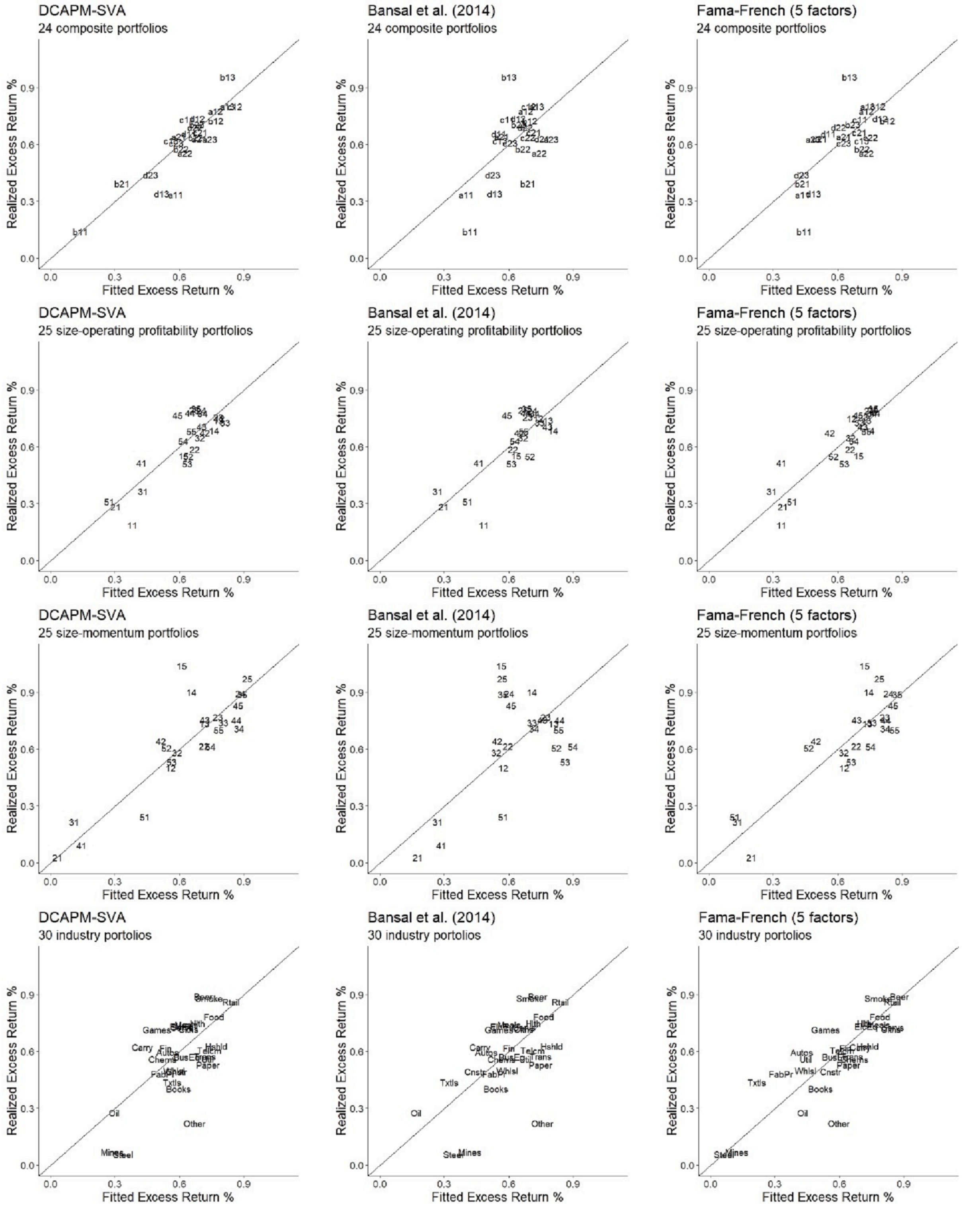
and returns (i.e. the factor betas).

In this regard, in order to estimate innovations in Equations (14) and (20), we follow Bansal et al. (2014) to use the residuals resulting from the VAR(1) specification of a vector of state variables comprising indicators that we assume investors use to shape their expectations. Specifically, to promote consistency with the models described in the previous section, our vector of state variables is composed of consumption growth (first release consumption growth for the DCAPM-SVA model and final consumption growth for the Bansal et al. (2014) model), the excess return on the market portfolio $RMRF_t$, the market price-dividend ratio for the US equity market (DP_t) determined using market data available on the Robert J. Shiller website, aggregate economic volatility $\widehat{V}_t$, and, in the case of the DCAPM-SVA model, the ambiguity factor f_t^A. Following Bansal et al. (2014), below we refer to this VAR specification as Macro VAR. Table 3 shows the main ordinary least squares (OLS) estimates for our Macro VAR.

As shown in Table 3, in general, our Macro VAR has small predictive power for most of the variables under consideration, with the exception of DP_t and $\widehat{V}_t$, which are strongly persistent over time. At this point, it should be noted that, contrary to Bansal et al. (2014), our sample covers monthly rather than annual observations, which largely explains the different results provided by our Macro VAR in forecasting consumption growth and macroeconomic volatility. As noted, in the next section we use the residuals resulting from these Macro VAR specifications to estimate innovations in the DCAPM-SVA model and the Bansal et al. (2014) model.

4. Results and discussion

In this section we describe the results provided by the model presented in Section 2, as well as those delivered by the models used as benchmarks. For that purpose, we follow the common practice in asset pricing to evaluate beta models by the mean absolute error (MAE), as well as the R^2 statistic and the *J*-test for overidentifying restrictions. However, as noted in recent research, the R^2 statistic



(caption on next page)

Fig. 1. Real vs. fitted values. Notes: Plots in the first row depict a set of double-sort portfolios, namely, 6 size-BE/ME portfolios, 6 size-momentum portfolios, 6 size-long-term reversal portfolios, and 6 size-short-term reversal portfolios. We represent each portfolio using a code with a letter and two numbers. Letter 'a' corresponds to size-BE/ME portfolios, letter 'b' corresponds to size-momentum portfolios, letter 'c' are size-long-term reversal portfolios, and letter 'd' are size-short-term reversal portfolios. The first number is the size code, where 1 represents portfolios comprising small firms and 2 portfolios comprising large firms. The second number denotes the tercile for the second sorting variable (i.e. BE/ME, momentum, long-term reversal or short-term reversal), with 1 representing the first tercile and 3 the last tercile. For the portfolios in the second and third row, there are two numbers, where the first number is the size code (with 1 being the smallest and 5 the largest) and the second number is the code for the second sorting variable (with 1 representing the first quintile and 5 the last quintile). The last row depicts the industry portfolios under analysis.

determined by OLS can lead to spurious results when used to evaluate linear asset pricing models. In this context, according to Lewellen et al. (2010), the R^2 statistic determined by generalized least squares (GLS) is more closely related to the mean–variance efficiency of the factor-mimicking portfolio than its OLS counterpart, which makes it a more challenging hurdle for evaluating linear asset pricing models. Accordingly, below we complement the R^2 statistic determined by OLS with the GLS R^2 statistic.

We estimate all models by mapping the two-pass cross-sectional regression method into the generalized method of moments (GMM). This approach allows us to simultaneously estimate all betas and lambdas in the pricing function, as well as correct the standard errors for the cross-sectional autocorrelation and for the fact that betas are generated regressors. Hence, following Cochrane (2005) (pp. 241–243), we use the following moment restrictions:

$$\mathbf{g_T}(\mathbf{b}) = \left\{ \begin{array}{c} \mathbf{E}\left(\mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t}\right) \\ \mathbf{E}\left[\left(\mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t}\right)\mathbf{X_t}\right] \\ \mathbf{E}\left(\mathbf{R_t^e} - \boldsymbol{\beta}\boldsymbol{\lambda}\right) \end{array} \right\} \tag{23}$$

where $\mathbf{X_t}$ is the vector of factors (i.e. in the case of the DCAPM-SVA model and the Bansal et al. (2014) model, the innovations that result from Macro VAR), and $\mathbf{a}$, $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ are parameters. In order to allow GMM to reproduce the two-pass cross-sectional regression approach, we use the following matrix to weight the moments in Equation (23) ($\mathbf{I}$ denotes the identity matrix):

$$\mathbf{a_T} = \begin{pmatrix} \mathbf{I}_{2N} & \\ & \boldsymbol{\beta}' \end{pmatrix} \tag{24}$$

so that:

$$\mathbf{a_T}\mathbf{g_T}\left(\widehat{\mathbf{b}}\right) = \mathbf{0}_{3N} \tag{25}$$

We determine the standard errors and establish the distribution of moments in Equation (23) using the standard GMM specification for linear asset pricing models (see Cochrane (2005) (pp. 203–204)), assuming a spectral density matrix $\mathbf{S}$ with zero leads and lags, as follows:

$$\mathbf{S} = \mathbf{E}\left\{ \left[\begin{array}{c} \mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t} \\ \left(\mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t}\right)\mathbf{X_t} \\ \mathbf{R_t^e} - \boldsymbol{\beta}\boldsymbol{\lambda} \end{array} \right] \left[\begin{array}{c} \mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t} \\ \left(\mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t}\right)\mathbf{X_t} \\ \mathbf{R_t^e} - \boldsymbol{\beta}\boldsymbol{\lambda} \end{array} \right]' \right\} \tag{26}$$

Table 4 summarizes the main results provided by the models under study. The table displays two rows for each model, where the first row shows the lambda estimates and the second row the t-statistics. For each model, the column labeled 'R^2' shows the OLS and GLS R^2 statistics, in that order, while the last column shows the results delivered by the J-test for overidentifying restrictions. On the other hand, Fig. 1 relates the average excess returns of the portfolios under study with the fitted values provided by the main models under study, where the closer the data points are to the 45-degree axis, the better the performance of the model, and vice versa.

Overall, the results in Table 4 show that the DCAPM-SVA model does a good job explaining the cross-sectional behavior of most of the portfolios under analysis, providing significantly higher R^2 statistics and a lower MAE than the Fama-French three-factor model. In fact, the DCAPM-SVA model outperforms the Fama-French five-factor model for the composite portfolios in Panel A and size-momentum portfolios in Panel C, while the Fama-French five-factor model delivers smaller pricing errors for size-operating profitability and industry portfolios. Furthermore, although the lambda coefficient for $\widehat{V}_t$ in the DCAPM-SVA model and the Bansal et al. (2014) model is not statistically significant in any panel, the lambda coefficient for ambiguity λ^A in the DCAPM-SVA model is statistically significant in all cases except for industry portfolios. In contrast, the classic C-CAPM and the CAPM exhibit poor performance in most cases, as expected.

In more detail, Panel A shows the results provided by the models under study for the set of 24 composite portfolios, as defined in the previous section, where the DCAPM-SVA model is the best performing model, providing an OLS R^2 statistic of 78.5% and a MAE of 0.06%. With a significantly lower OLS R^2 statistic (51.4%) and a MAE of 0.09%, the Fama-French five-factor model is the second-best performer, followed by the Bansal et al. (2014) model, which provides an OLS R^2 statistic and a MAE of 31.2% and 0.12%, respectively. Nonetheless, despite the relatively poor performance of the Bansal et al. (2014) model, it should be noted that macroeconomic volatility allows the model to significantly outperform the classic C-CAPM. In fact, with an OLS R^2 statistic of 1.3% and a MAE of

0.13%, the C-CAPM is the worst performing model, followed by the classic CAPM.

Importantly, ambiguity, as measured by f_t^A in Equation (22), is the factor that implies a greater improvement in the results delivered by the consumption-based asset pricing models in Table 4, Panel A, allowing the DCAPM-SVA model to more than double the OLS R^2 statistic of the Bansal et al. (2014) model, and halve the MAE. In this regard, it is important to note that the price of risk for ambiguity amounts to a statistically significant value of 0.003, which means that those stocks that covary positively with f_t^A provide a higher expected return.

Nevertheless, despite the apparent superiority of the DCAPM-SVA model in pricing composite portfolios, its GLS R^2 statistic (35.2%) drops sharply with respect to its OLS counterpart (78.5%), meaning that its factor-mimicking portfolio is far from mean-variance efficient. Moreover, the *J*-test for overidentifying restrictions rejects all models in Table 4, Panel A, under the specifications described above. In this regard, the plots in the first row of Fig. 1 show that, while the pricing errors delivered by the DCAPM-SVA model exhibit a relative dispersion considering their small absolute value, both the Bansal et al. (2014) model and the Fama-French five-factor model provide scattered data points, which largely explains the results of the *J*-test for overidentifying restrictions.

While these patterns largely persist for size-operating profitability portfolios in Table 4, Panel B, there are some differences that should be highlighted. First, the market factor models under study, that is, the CAPM and the Fama-French three- and five-factor models, perform significantly better in pricing size-operating portfolios in Panel B than composite portfolios in Panel A. Thus, the Fama-French five-factor model provides the highest OLS R^2 statistic in Panel B (79.6%) of all the models under analysis, while the CAPM delivers an acceptable OLS R^2 statistic of 40.4%, which is sensibly higher than its equivalent in Panel A (11.2%). Second, macroeconomic volatility allows the Bansal et al. (2014) model to provide an OLS R^2 statistic of 64.9%, that is, more than 64% higher than the result delivered by the classic C-CAPM (0.6%). Hence, considering that the DCAPM-SVA model provides an OLS R^2 statistic of 72.7% in Panel B, macroeconomic volatility seems more explanatory than ambiguity to price size-operating profitability portfolios, which contrasts with the results in Panel A for composite portfolios. In any case, the DCAPM-SVA model is the second-best performing model in Panel B, following the Fama-French five-factor model. Moreover, although the GLS R^2 statistics of the DCAPM-SVA model and the Bansal et al. (2014) model fall sharply with respect to their OLS counterparts, the *J*-test for overidentifying restrictions fails to reject these models, while it rejects the other models in Panel B. Furthermore, the lambda coefficient for ambiguity remains statistically significant, with a value (0.002) relatively close to that shown in Panel A (0.003).

Although momentum portfolios have typically represented a challenging hurdle for most asset pricing models (see Fama and French (1993) and Roh et al. (2019)), the results in Table 4, Panel C, show that the DCAPM-SVA model does a good job in pricing size-momentum portfolios. In fact, with an OLS R^2 statistic of 81.6% and a MAE of 0.09%, the DCAPM-SVA model is the best performing model in Panel C, followed by the Fama-French five-factor model with an OLS R^2 statistic and a MAE of 77.1% and 0.11%, respectively. As in Panel A, ambiguity exhibits strong explanatory power in determining the expected returns of size-momentum portfolios, allowing the DCAPM-SVA model to increase its OLS R^2 statistic by more than 30% with respect to the Bansal et al. (2014) model, which provides an OLS R^2 statistic and a MAE of 49.3% and 0.17%, respectively. Furthermore, as in Panels A and B, the lambda coefficient for ambiguity remains statistically significant and equal to 0.002, which supports the robustness of the results. In contrast, macroeconomic volatility exhibits less explanatory power, allowing the Bansal et al. (2014) model to increase the OLS R^2 statistic by 13.5% with respect to the classic C-CAPM. Remarkably, the *J*-test for overidentifying restrictions fails to reject the DCAPM-SVA model in Panel C, while it rejects the other models under study.

Panel D in Table 4 shows that, in general, macroeconomic volatility and ambiguity imply small increases in the explanatory power of consumption models when estimating the expected returns of industry portfolios. In this case, the DCAPM-SVA model provides an OLS R^2 statistic of 66.5% and a MAE of 0.13%, slightly outperforming the Bansal et al. (2014) model (with an OLS R^2 statistic and a MAE of 60% and 0.14%, respectively) and the C-CAPM (with an OLS R^2 statistic of 58.4% and a MAE of 0.14%). However, this lower performance is common to most of the other models under study, except for the Fama-French five-factor model, which provides an OLS R^2 statistic and a MAE of 71.9% and 0.1%, respectively. Thus, while the Fama-French three-factor model provides an OLS R^2 statistic of 46.9% and a MAE of 0.14%, these statistics amount to 12.3% and 0.18% in the case of the CAPM. Nevertheless, the results in Panel D are consistent with those provided by a large part of the previous research on the area, which generally obtains poor results for industry portfolios due to imprecise estimates of risk premiums and risk loadings across industries, and the weak factor structure of industry portfolios (Fama & French, 1997; Lewellen et al., 2010). In fact, this is the only case among those considered in Table 4 where the lambda coefficient for ambiguity is not statistically significant.

In any case, despite the poor performance of the models under analysis in pricing industry portfolios, it should be noted that the *J*-test for overidentifying restrictions fails to reject all models in Table 4, Panel D. However, these results should be taken with caution, as non-rejection is mainly due to the high variance of pricing errors rather than low absolute pricing errors, as shown in plots depicted in the last row of Fig. 1.

In general, our results show that ambiguity, measured according to the Borup and Schütte (2021) model, contributes satisfactorily to complementing the theoretical framework developed by Bansal et al. (2014) to account for the effects of macroeconomic fluctuations on expected returns. Thus, the results of the model are significantly improved when we introduce ambiguity as an additional pricing factor, which allows the DCAPM-SVA model to outperform most models that are typically used for comparison purposes in the asset pricing literature. Furthermore, the lambda coefficient for ambiguity λ^A remains positive, statistically significant and nearly invariant for the vast majority of portfolios that constitute our test assets, meaning that those assets that covary positively with the ambiguity factor f_t^A exhibit higher expected returns, and vice versa.

Regarding macroeconomic volatility, the prices of risk in Table 4 are not statistically significant for any of the portfolios under consideration, delivering positive or negative risk premiums depending on the model and the specific asset. In particular, although the lambda coefficient for macroeconomic volatility is always negative in the DCAPM-SVA model, it takes a positive value for size-operating profitability portfolios and industry portfolios in the Bansal et al. (2014) model. These results contrast with those obtained by Bansal et al. (2014), who find a positive risk premium for volatility risk exposure. However, it should be noted that, for the DCAPM-SVA model, we estimate macroeconomic volatility using the first release consumption in Equation (21) instead of final consumption, which can partially explain these disparities. Moreover, the size and periodicity of the time rolling window used to determine $\widehat{V}_t$, as well as the time period and the specific assets used to conduct the study, may also explain such divergences.

Additionally, it is important to note that our data series include the period of economic turmoil due to the pandemic, which has been characterized by a sharp drop in consumption and an important increase in volatility. In this context, our results not only show that the Bansal et al. (2014) model and, especially, the DCAPM-SVA model allow to adequately capture the variation in expected returns across assets, but also that other prominent asset pricing models, such as the Fama-French three-factor model, appear to fit excess returns with higher pricing errors than in previous research. In this regard, our results are consistent with the findings of Wang (2022), who shows that ambiguity aversion can result in an amplification of financial crises, as well as with the results of Dlugosch and Wang (2022), who find that investors may decide to hold a greater or lesser proportion of risky assets in their portfolios depending on the level of ambiguity, which suggests that ambiguity works partially as a channel of information quality.

5. Conclusion

Recent research on asset pricing highlights the importance of macroeconomic volatility and ambiguity in explaining the dynamics of stock returns. Combining the model proposed by Bansal et al. (2014) with the measure of ambiguity suggested by Borup and Schütte (2021), we develop a four-factor asset pricing model that captures a large fraction of the cross-sectional variation of excess returns for a wide range of market anomaly portfolios, outperforming some prominent asset pricing models, such as the Fama-French three-factor model and, in some cases, the Fama-French five-factor model.

Furthermore, our results show that the price of risk for ambiguity is positive and statistically significant for the vast majority of the portfolios that constitute our test assets, meaning that those assets that covary positively with the ambiguity factor provide higher expected returns to compensate investors for the higher uncertainty, and vice versa. Regarding macroeconomic volatility, although the price of risk for the variance of consumption growth is not statistically significant in any of the portfolio sorts considered in our study, its effect on the explanatory power of both the Bansal et al. (2014) model and the DCAPM-SVA model is greater than that of ambiguity for some specific assets, such as size-operating profitability portfolios. These results suggest that macroeconomic volatility and ambiguity complement each other to explain different sorts of market anomaly portfolios. Although the study of the asset characteristics that explain the different exposure of stocks to macroeconomic volatility and the ambiguity factor is beyond the scope of this paper, further research on this subject is mandatory.

Our results are consistent with investors concerned about the credibility of their expectations on macroeconomic variables such as consumption growth. Thus, at times of economic turmoil, when the economic environment is less predictable, agents must learn more rapidly to include the available information into their estimates, which increases ambiguity, with the consequent effects on asset prices. Additionally, our results highlight the importance of vintage data on aggregate consumption for asset pricing, as they capture short-term dynamics that are lost in final consumption series, consistent with Borup and Schütte (2021).

CRediT authorship contribution statement

Rubén Lago-Balsalobre: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Visualization, Writing – original draft. **Javier Rojo-Suárez:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ana B. Alonso-Conde:** Conceptualization, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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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.

Data availability

Data will be made available on request.

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