Business-Cycle Variation in Macroeconomic Uncertainty and the Cross-Section of Expected Returns: Evidence for Horizon-Dependent Risks[*]

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Abstract

A single factor that captures assets' exposure to business-cycle variation in macroeconomic uncertainty can explain the level and cross-sectional differences of asset returns. Specifically, based on portfolio-level tests I demonstrate that uncertainty shocks with persistence ranging from 32 to 128 months carry a negative price of risk of about -2% annually. The price of risk for innovations in the raw series of aggregate uncertainty and for high-frequency fluctuations is insignificant. Also, equity exposures are negative and hence risk premia are positive. I quantify macroeconomic uncertainty using the model-free index of Jurado et al. (2015) derived from monthly, quarterly and annual forecasts.

Keywords: *macroeconomic uncertainty, scale-wise heterogeneity, horizon-dependent risks, monotonicity of factor loadings*

JEL classification: E32, E44, G12, C22

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1 Introduction

In this paper, I decompose macroeconomic uncertainty into components with heterogeneous degrees of persistence and investigate the price of risk and the uncertainty premia associated with each of these horizon-dependent macroeconomic shocks. This approach allows me to identify a close link between macroeconomic uncertainty and portfolio expected returns at business-cycle frequencies which is not present in the raw series. I quantify aggregate uncertainty using the model-free index of Jurado et al. (2015) that measures the common variation in the unforecastable component of a large number of economic indicators. That is, in line with the core intuition of Jurado et al. (2015) I start my empirical work from the premise that what matters for consumption and investment decisions is not if the conditional volatility of a particular macroeconomic indicator has become more or less dispersed. Instead, what is important is whether the state of the economy is more or less predictable. To classify uncertainty shocks into layers with different levels of persistence (i.e. on the basis of their arrival time and scale) I rely on the multiresolution-based decomposition for weakly stationary time series of Ortu et al. (2013). Moreover, my study is based on the novel framework for scale-based (i.e. horizon-specific) analysis of risk as proposed first in Bandi and Tamoni (2015) and extended later by Boons and Tamoni (2015).

I find that a single *business-cycle*[1] *uncertainty* factor that captures assets' exposure to low-frequency variation in aggregate uncertainty can help explain the level and the cross-sectional differences of asset returns. In particular, based on portfolio-level tests I show that uncertainty shocks

[1]Business-cycle dynamics correspond to periods of roughly 2-8 years - see Burns and Mitchell (1946) and the survey of Diebold and Rudebusch (1996). More recently, Comin and Gertler (2006) argue that business cycles are more persistent phenomena and suggest modelling fluctuations beyond 8 years.

with persistence ranging from 32 to 128 months carry a negative price of risk of about -2% annually. The price of risk for high-frequency fluctuations and for the innovations in the raw series of aggregate uncertainty (see Table B.1) is not significant. In addition, I demonstrate that equity exposures to macroeconomic uncertainty are also negative and hence uncertainty risk premia are positive. My results remain statistically significant after using a t-statistic cutoff of three as suggested by Harvey et al. (2016) and are quantitatively similar irrespective of whether uncertainty is derived from 1, 3 or 12 months ahead forecasts. Furthermore, while misspecification is an inherent feature of several prominent asset pricing models (for instance, see Kan et al., 2013 and Gospodinov et al., 2014) I show that the one-factor model with business-cycle macro uncertainty is correctly specified. This finding is an important contribution in the existing literature.

My work follows and builds upon the novel work of Boons and Tamoni (2015) that emphasizes the importance of low-frequency macro volatility shocks with persistence greater than 4 years in determining asset prices. In comparison with Boons and Tamoni (2015) I do not restrict[2] the price of risk across scales and hence my empirical results are more precise about the exact horizon over which macroeconomic uncertainty matters (i.e. 32 to 128 months). In particular, I document that only business-cycle variation in uncertainty drives asset prices. Fluctuations in macro uncertainty with persistence greater than 128 months are not consistently priced in the cross-section of expected returns (see Tables IA.5 - IA.7). In addition, I show that the quarterly results for macro volatility risk in Boons and Tamoni (2015) are not robust to changes in the sampling frequency. Specifically, using monthly data I find that low-frequency shocks in the volatility of industrial production are

[2]Note that I estimate separately the price of risk for each horizon (i.e. I analyze the entire term structure if risk prices). Boons and Tamoni (2015) focus on a more traditional (in the spirit of Beveridge and Nelson, 1981) separation of high versus low-frequency components, i.e. they estimate a restricted two-factor model.

not priced at the portfolio level (see Table IA.8). On the contrary, my estimates for the price of risk are free from dependencies on any single economic indicators, numerically similar (i.e. -2%) and robust across different test assets including: the 25 Fama and French (1993) size and book-to-market portfolios, the 25 Fama and French (2015b) size and investment portfolios, the 25 Fama and French (2015b) book-to-market and operating profitability portfolios and the 25 Fama and French (2015a) size and variance portfolios. Also, my results suggest that the uncertainty shocks at each scale carry unique information[3] (i.e. *scale-wise heterogeneity*). That is, in the spirit of Bandi et al. (2015) there is a simple statistical explanation of why the relation between macro uncertainty and returns is only present at certain horizons.

Moreover, I find that the horizon-specific risk loadings are increasing monotonically for portfolios sorted on size and investment. An increase in low-frequency uncertainty has a smaller effect on large firms and aggressive firms and hence these securities offer smaller risk compensations - consistent with the well-known size effect (i.e. one-period average returns decrease from small to big stocks) and the investment effect (i.e one-period average returns decrease from conservative to aggressive stocks), respectively. Similarly, horizon-specific risk exposures decrease monotonically across book-to-market and dividend-yield - consistent with the well-documented value and dividend-yield effects. Overall, I document a low-frequency risk-return trade-off for the valuation of portfolios exposed to fluctuations in macroeconomic uncertainty.

My work adds to a new strand of research that examines how horizon-dependent shocks propagate to asset prices. Bandi et al. (2015) introduce the novel notion of scale-specific predictability and demonstrate its significance as a channel through which economic relations may be valid at partic-

[3] Similar results in Bandi et al. (2015) for market variance and consumption variance.

ular horizons (i.e. levels of resolution) without having to be satisfied at all horizons. Ortu et al. (2013) decompose consumption growth into components with heterogeneous levels of persistence and analyze their implications within a Bansal and Yaron (2004) style economy. Bandi and Tamoni (2015) show that fluctuations in consumption growth between 2 and 8 years can explain the differences in risk premia across book-to-market and size-sorted portfolios in line with the Consumption CAPM. In a similar fashion, Kamara et al. (2015) study the pricing of Fama-French factors across investment horizons. Noteworthy contributions in this area also include Yu (2012) and Dew-Becker and Giglio (2015) who analyze the joint properties of returns and macroeconomic growth at different frequencies.

Furthermore, my work contributes to a voluminous literature that analyzes the determinants of the cross-section of stock returns. For surveys of empirical literature on cross-sectional asset pricing see Subrahmanyam (2010), Goyal (2012) and more recently Harvey et al. (2016). Within this body of work two main lines of research are related to my study. The first part seeks to explain the cross-sectional pattern in returns based on the insights of the long-run risks (LRR) model of Bansal and Yaron (2004) which combines consumption and dividend growth rate dynamics governed by persistent shocks and fluctuating economy uncertainty[4]. In line with Boons and Tamoni (2015), my study focuses on the covariance of long-term returns with innovations in long-term uncertainty and hence is distinct from the LLR framework which quantifies assets' exposure to long-run risks using one-period returns.

The second branch of this literature relies on the intuition of Merton's (1973) intertemporal

[4]Due to the resulting low-frequency properties of the time series of aggregate consumption and dividends this family of models is known as long-run risks models. For econometric estimation techniques see Constantinides and Ghosh (2011) and Grammig and Schaub (2014) and for the out-of-sample performance Ferson et al. (2013).

capital asset pricing model (ICAPM) to test for pricing of macroeconomic factors. In a seminal paper, Merton (1973) demonstrates that in a multi-period economy investors have incentives to hedge against future stochastic shifts in the investment and consumption opportunity sets. This implies that state variables that are correlated with changes in investment opportunities play an important role in determining asset returns.

Recent studies suggest that macroeconomic uncertainty can also be thought of as a state variable within the context of the ICAPM proxying for future investment and consumption opportunities. In particular, Ozoguz (2009) shows that investors' uncertainty about the state of the economy can help explain the time-series variation in stock returns and their cross-sectional properties. Bali et al. (2015) develop a simple extension of Merton's (1973) conditional asset pricing model with economic uncertainty and show that uncertainty betas can explain the dispersion in individual stock returns while Bali et al. (2014) demonstrate that macroeconomic risk is priced in the cross-section of hedge funds. My work adds in this line of research in the following ways: First, I extend the study of Bali et al. (2015) by demonstrating that only fluctuations in macroeconomic uncertainty with persistence ranging from 32 to 128 months are consistently priced in the cross-section of portfolio returns while short-lived fluctuations and the innovations in the raw series are not. Second, I document that future excess aggregate returns are positively correlated with past uncertainty and thus the negative price of risk for exposure to business-cycle macro uncertainty is inconsistent with the central economic intuition underlying the ICAPM. That is, in the spirit of Maio and Santa-Clara (2012) and Boons (2015) macroeconomic uncertainty is not a valid risk factor under the ICAPM.

The remainder of this paper is organized as follows: Section 2 provides the empirical analysis, including the extraction of the persistent components and cross-sectional regressions. Section 3 contains robustness checks and additional tests while Section 4 examines the monotonicity of the horizon-specific risk exposures. Section 5 concludes. For additional information on how to test for monotonic patterns in factor risk loadings see Appendix A.

2 Empirical Analysis

2.1 Data Description

To measure macroeconomic uncertainty I use the model-free index of Jurado et al. (2015) that aggregates uncertainty in the economy derived from various sources into one summary statistic. Jurado et al. (2015) combine 132 macroeconomic series and 147 financial time series together into one large macroeconomic dataset[5] to provide a new measure of macroeconomic uncertainty defined as the common variation in the unforecastable components. The first dataset (also used in Ludvigson and Ng, 2009) represents a broad category of macroeconomic time series such as: real output and income, employment, consumer spending, bond and stock market indexes and foreign exchange measures. The second dataset (also used in Ludvigson and Ng, 2007) includes valuation ratios such as dividend-price ratio and earnings-price ratio, default and term spreads, yields on corporate bonds and a large cross-section of equity returns.

In particular, let $u_{i,t}(h)$ denote the $h-$period ahead uncertainty in the variable $y_{i,t} \in Y_t = (y_{1,t}, \ldots, y_{Ny,t})^{'}$ defined as the conditional volatility of the unforecastable component of its future value, that is,

[5]The dataset is available from Sydney Ludvigson's website: http://www.econ.nyu.edu/user/ludvigsons/ .

$$u_{i,t}(h) \equiv \sqrt{E\left[\left(y_{i,t+h} - E\left[y_{i,t+h}|I_t\right]\right)^2 |I_t\right]} \tag{1}$$

where I_t is the information set[6] available to investors at time t. Jurado et al. (2015) construct the index of macroeconomic uncertainty by aggregating individual uncertainty at each date, i.e. the $h-$period ahead aggregate uncertainty at time t is given by

$$u_t(h) \equiv \text{plim}_{Ny\to\infty} \sum_{i=1}^{Ny} w_i u_{i,t}(h) \equiv E_w\left[u_{i,t}(h)\right] \tag{2}$$

where $w_i = 1/N_y$ are aggregation weights. I rely on estimates of aggregate uncertainty derived from 1, 3 and 12 months ahead forecasts. Throughout the paper I use the notation u_t for the time series proxying for macroeconomic uncertainty leaving h understood when there is no chance of confusion.

[Insert Table 1 about here.]

In Panel A of Table 1 I report descriptive statistics for the macroeconomic uncertainty index. In addition, I examine the persistence of the uncertainty index through a battery of testing procedures. The null hypothesis of a unit root is rejected at the 5% level with the Augmented Dickey-Fuller (ADF - Dickey and Fuller, 1979) and Phillips-Perron (PP - Phillips and Perron, 1988) tests for all measures of uncertainty. Similarly, the results of a KPSS (Kwiatkowski et al., 1992) test for the null hypothesis of stationarity whose critical values are 0.347, 0.463 and 0.739 at the 10%, 5% and 1% significance levels respectively confirm that the series is stationary for all $h = 1, 3, 12$. Panel B

[6] To estimate $E\left[\cdot|I_t\right]$ Jurado et al. (2015) form factors from a large set of predictors whose span is close to I_t and approximate $E\left[\cdot|I_t\right]$ using the method of diffusion index forecasting (see Stock and Watson, 2002).

of Table 1 presents the mean and standard deviation for the equity risk premium[7], defined as the total rate of return on the stock market minus the prevailing short-term interest rate. Over the sample period it has a mean of 5.71% and a standard deviation of 15.02%. Figure 1 plots the index of macroeconomic uncertainty for $h = 1, 3, 12$. The shaded areas represent NBER recessions.

[Insert Figure 1 about here.]

2.2 Scale-wise Heterogeneity in Aggregate Uncertainty

I begin by decomposing uncertainty into layers with heterogeneous levels of persistence using the multiresolution-based decomposition of Ortu et al. (2013). In particular, let $u_t^{(j)}$ denote fluctuations of the uncertainty series with half-life in the interval $[2^{j-1}, 2^j)$, that is

$$u_t^{(j)} = \frac{\sum_{i=0}^{2^{(j-1)}-1} u_{t-i}}{2^{(j-1)}} - \frac{\sum_{i=0}^{2^j-1} u_{t-i}}{2^j} \equiv \pi_t^{(j-1)} - \pi_t^{(j)} \tag{3}$$

where $j \geq 1$, $\pi_t^{(0)} \equiv u_t$ and the moving averages $\pi_t^{(j)}$ satisfies the recursion

$$\pi_t^{(j)} = \frac{\pi_t^{(j-1)} - \pi_{t-2^{j-1}}^{(j-1)}}{2} \tag{4}$$

for $j = 1, 2, 3, \ldots$. The derived series $\left\{u_t^{(j)}\right\}_{t\in\mathbb{Z}}$ captures fluctuations that survive to averaging over 2^{j-1} terms but disappear when the average involves 2^j terms. For any $J \geq 1$, the original series u_t can be written as a sum of components with half-life belonging to a specific interval plus a long-run average, that is,

[7] The data for the equity risk premium and the default and term spread used in Section 2.4 are available from Amit Goyal's website: http://www.hec.unil.ch/agoyal/

$$u_t = \sum_{j=1}^{J} u_t^{(j)} + \underbrace{u_t^{(>J)}}_{\equiv \pi_t^{(J)}} \tag{5}$$

where $u_t^{(>J)}$ incorporates fluctuations with persistence greater than 2^J periods. The decomposition of the time series is conducted using wavelet methods as in multiresolution analysis. In particular, the extraction is based on the one-sided, linear Haar filter. Moreover, the decomposition in Equation (5) uses information only up to time t and hence is not subject to look-ahead bias. In contrast, other popular filters for business cycle analysis are estimated over the full sample (for instance, see Hodrick and Prescott, 1997).

For my empirical analysis, I set $J = 7$ so that the maximum level of persistence corresponds to the upper bound of business cycle frequencies. An interpretation of the $j-$th persistence level in terms of the corresponding time spans in the case of monthly time series is available in Panel C of Table 1. Figure 2 depicts the persistent components filtered out of aggregate uncertainty. Due to the initialization of the filtering procedure I discard the first $2^j - 1$ observations for each scale.

[Insert Figure 2 about here.]

Furthermore, I use the multi-scale variance ratio test of Ortu et al. (2013) to test for serial correlation in the extracted uncertainty components $u_t^{(j)}$, $j = 1, 2, \ldots, 7$. This test is based on a new family of frequency-domain tests for serial correlation as introduced by Gençay and Signori (2015) and exploits the fact that for a serial correlated process each component contributes a different percentage to the variance of the process[8]. Specifically, let $\hat{\xi}_j$ be the ratio of the sample variance of

[8]Theorem 3 in Gençay and Signori (2015) states that for a stationary white noise process the wavelet variance at

the uncertainty components at level of persistence j to the sample variance of the time series, i.e.

$$\hat{\xi}_j = \frac{2^j \left(\mathbf{u^{(j)}}\right)^\intercal \mathbf{u^{(j)}}}{\left(X_T^{(J)}\right)^\intercal X_T^{(J)}} \tag{6}$$

where $\left(X_T^{(J)}\right)^\intercal = [u_T, u_{T-1}, \ldots, u_1]$ is the vector collecting the observations of $\{u_t\}$ and $\mathbf{u^{(j)}} = \left[u_{2^j}^{(j)}, \ldots, u_{k\times 2^j}^{(j)}, \ldots, u_T^{(j)}\right]^\intercal$. That is, due to the overlapping of the moving averages that define $u_t^{(j)}$ the elements of each component are first sampled every $k \times 2^j, k \in \mathbb{Z}$ times and thus the sample variance is calculated from the decimated series[9]. Under the null hypothesis of no serial correlation, the rescaled test statistic $\sqrt{\frac{T}{a_j}}\left(\hat{\xi}_j - \frac{1}{2^j}\right)$ where $a_j = \frac{\binom{2^j}{2}}{2^j 2^{2(j-1)}}$ converges in distribution to a standard normal. Ortu et al. (2013) suggest employing these rescaled test statistics to distinguish a white noise process from a process whose (decimated) scale-dependent components are serially correlated. Table 2 presents the results for the variance ratio test of Ortu et al. (2013) for different levels of persistence with bold values denoting rejection of the null at a 99% confidence level. A white noise model is strongly rejected at multiple levels of persistence. These results imply that at least one of the uncertainty components can be represented as a scale autoregressive process on the dilated time of the scale being considered. In other words, there exists $j^* \in \{1, \ldots, 7\}$ such that $u_{k\times 2^{j^*}+2^{j^*}}^{(j^*)} = \rho_{j^*} u_{k\times 2^{j^*}}^{(j^*)} + \varepsilon_{k\times 2^{j^*}+2^{j^*}}^{(j^*)}$ where $k \in Z$ and the parameter ρ_j captures scale-specific persistence - known as scale-wise AR. Estimation results of the multi-scale autoregressive system are available in the Internet Appendix (see Table IA.17).

scale m contributes a ratio of 2^{-m} to the total variance. Any departure from this benchmark provides the means to detect serial correlation.

[9]Decimation is the process of defining *non-redundant* information contained in the observed components. As a result, essential information in the extracted components can be summarized by a finite number of non-overlapping points. For more information - including the size and power properties of the multi-scale variance ratio test - see Ortu et al. (2013).

In total, the empirical evidence in this section provide strong support for a data generating process in which low-frequency uncertainty shocks are not linear combinations of high-frequency shocks. That is, in line with the generalized Wold representation of Bandi et al. (2015) the uncertainty shocks at each scale carry unique information (i.e. scale-wise heterogeneity) - *thereby giving meaning to economic relations which may be satisfied at certain horizons alone*. Moreover, innovations for all horizon-specific uncertainty shocks have to be computed before examining their asset pricing implications (i.e. only the unexpected part of the uncertainty shocks should command a risk premium).

[Insert Table 2 about here.]

2.3 Cross-sectional Implications

I test whether the innovations (i.e. $\Delta u_t^{(j)} \equiv u_t^{(j)} - u_{t-1}^{(j)}$) in the persistent components filtered out of the uncertainty index can help explain the cross-sectional variation in asset prices. This approach resembles empirical studies that test ICAPM-motivated macroeconomic factors by calculating innovations in state variables. To obtain the innovations for each scale j, I first extract the $j-$th component and then I first-difference it. Under the one-sided, linear Haar filter used in the extraction, first-differencing the component of a given time series is identical to taking components of the first-differenced series (see Bandi et al., 2015).

Macroeconomic risk as proxied by the covariance between innovations in uncertainty (i.e. Δu_t) and asset excess returns (i.e. $R_t^{e,i}$) can be decomposed across scales as follows (see the novel framework of Bandi and Tamoni, 2015 and Boons and Tamoni, 2015)

$$Cov\left[R_t^{e,i}, \Delta u_t\right] = \sum_{j=1}^{J} Cov\left[R_t^{e,i(j)}, \Delta u_t^{(j)}\right] + Cov\left[R_t^{e,i(>J)}, \Delta u_t^{(>J)}\right] \tag{7}$$

and hence the scale-wise (i.e. horizon-specific) risk exposures are defined as

$$\beta^{i(j)} \equiv \frac{Cov\left[R_t^{e,i(j)}, \Delta u_t^{(j)}\right]}{Var\left(\Delta u_t^{(j)}\right)} \quad \text{and} \quad \beta^{i(>J)} \equiv \frac{Cov\left[R_t^{e,i(>J)}, \Delta u_t^{(>J)}\right]}{Var\left(\Delta u_t^{(>J)}\right)}. \tag{8}$$

In particular, in line with Boons and Tamoni (2015) I first run for each asset i (of size T) the following time-series regression

$$R_t^{e,i(j)} = \beta_0^{(j)} + \beta^{i(j)} \Delta u_t^{(j)} + \varepsilon_t^{(j)} \quad t = 1, \ldots, T \text{ for each } j = 1, \ldots, 7, > 7, \tag{9}$$

where ${R_t}^{e,i(j)}$ denotes the components of asset excess returns associated with scale j at time t. Then I estimate a cross-sectional regression of average portfolio returns on the estimated horizon-specific risk exposures $\beta^{i(j)}$

$$\overline{R^{e,i}} = \lambda_{0,j} + \lambda_j \beta^{i(j)} + \alpha_i \quad \text{for each } j = 1, \ldots, 7, > 7, \tag{10}$$

where $\overline{R^{e,i}}$ denotes the average time-series excess return for asset i, $\lambda_{0,j}$ is the zero-beta excess return associated with different uncertainty components, λ_j is the relative price of risk for $\beta^{(j)}$ (i.e. the horizon-specific risk compensation)[10] and α_i is a pricing error. In essence, I am interested in the ability of horizon-dependent uncertainty shocks to explain aggregate portfolio returns. In addition, I run Equations (9)-(10) for uncertainty shocks with persistence between 32 and 128 months (i.e.

[10]The last term in Equation (7) vanishes as $J \to \infty$. I verify empirically that for $j > 7$ and for all test portfolios, assets' exposure to uncertainty shocks with persistence greater than $2^7 = 128$ months is not important for pricing. The results are available in the Internet Appendix (see Tables IA.5, IA.6 and IA.7).

for a *business-cycle uncertainty* factor) where the corresponding beta for $j = 6:7$ is defined as

$$\beta^{i(6:7)} \equiv \frac{Cov\left[R_t^{e,i(6)} + R_t^{e,i(7)}, \Delta u_t^{(6)} + \Delta u_t^{(7)}\right]}{Var\left(\Delta u_t^{(6)} + \Delta u_t^{(7)}\right)} \simeq \beta^{i(6)}\varpi^{(6)} + \beta^{i(7)}\varpi^{(7)} \tag{11}$$

with $\varpi^{(6)} = \frac{Var\left(\Delta u_t^{(6)}\right)}{Var\left(\Delta u_t^{(6)}\right)+Var\left(\Delta u_t^{(7)}\right)}$ and $\varpi^{(7)} = \frac{Var\left(\Delta u_t^{(7)}\right)}{Var\left(\Delta u_t^{(6)}\right)+Var\left(\Delta u_t^{(7)}\right)}$. That is, $\beta^{(6:7)}$ can be viewed as a linear combination[11] of the betas associated with the factors $\Delta u_t^{(6)}$ and $\Delta u_t^{(7)}$ with weights depending on the relative contribution to total variance (see also Bandi and Tamoni, 2015 for a similar approach using decimated components).

Following Campbell et al. (2014) and in line with the theoretical work of Black (1972) and the evidence[12] in Krishnamurthy and Vissing-Jorgensen (2012) I leave the zero-beta risk-free rate unrestricted. To determine whether uncertainty shocks with level of persistence j can explain the cross-sectional variation in asset returns I look for an estimate $\hat{\lambda}_j$ that remains significant after using a t-statistic cutoff of three as suggested by Harvey et al. (2016), for an intercept that is small and statistically insignificant and a sample R^2 significantly different from zero.

[Insert Table 3 about here.]

Table 3 presents the first-pass beta estimates for the 25 Fama and French (1993) size and book-to-market portfolios along with their statistical significance. The initial sample period is 1960:07 to 2013:05. The betas are estimated component-wise from Equation (9), that is regressing the $j-$th

[11] Asymptotically, the components are uncorrelated across scales. In sample, however, multiresolution filters - like the Haar filter used for the extraction - only deliver *nearly-uncorrelated* components (see also Bandi and Tamoni, 2015 and Gençay et al., 2001) and therefore the relation in Equation (11) is not exact. For further discussion and a comparison of $\beta^{(6:7)}$ versus $\beta^{(6)}\varpi^{(6)} + \beta^{(7)}\varpi^{(7)}$ see the Internet Appendix (see Figure IA.2).

[12] Krishnamurthy and Vissing-Jorgensen (2012) suggest that investors' demand for Treasury Bills is driven by liquidity and safety concerns and argue against the common practice of identifying the Treasury Bills as risk-free interest rates.

component of returns on innovations in the $j-$th component of aggregate uncertainty. Given the adopted time-series decomposition spurious autocorrelation at level of persistence j emerges as a result of the 2^j-1 overlapping data. Thus, I compute Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors with 2^j-1 lags. To preserve space I only report results[13] for $j=6,7$ and $j=6:7$. The horizon-specific risk exposures for the test portfolios are negative. The last rows of Table 3 show the Wald test-statistics and their corresponding p-values from testing the joint hypothesis that all horizon-dependent exposures are equal to zero. For $j=6$ and $j=6:7$ the null hypothesis in the joint test of significance i.e. $H_0:\ \beta^{1(j)}=\ldots=\beta^{25(j)}=0$ is strongly rejected. Therefore, in the spirit of Kan and Zhang (1999) it is empirically sound to use these scale-dependent betas as factors in cross-sectional regressions. In contrast, for $j=7$ I cannot reject the null that the horizon-specific risk exposures are jointly zero.

[Insert Table 4 about here.]

Table 4 reports the estimates for the zero-beta excess return and the price of risk for each scale for the 25 size and book-to-market portfolios along with the corresponding Fama-MacBeth[14] (1973) test statistics in parentheses. In addition, I normalize the scale-wise risk exposures and estimate the price of risk per unit of cross-sectional standard deviation in uncertainty in percent per year. I also report the p-value for the Kan et al. (2013) specification test of $H_0:\ R^2=1$ denoted as $p\left(\mathrm{R}^2=1\right)$. After taking into consideration the data-mining adjusted rate for t-statistics of three, the lambda estimates for levels of persistence $j=1,\ldots,5$ are insignificant. The estimated price

[13]For $j\in\{1,2,3,4,5\}$ the horizon-specific risk exposures are jointly different from zero across all test assets (results available upon request).

[14]Given that the first-stage regressions are scale-wise, the Shanken correction (Shanken, 1992) is not directly applicable here. To deal with the error-in-variables problem (i.e. the estimation errors in the betas) I report bootstrapped confidence intervals for the second-pass estimates in the Internet Appendix (Table IA.14).

of risk for the innovations in the sixth uncertainty component $\hat{\lambda}_6$ is -0.69 with a t-statistic of -4.57 while the intercept is 0.14 and insignificant (t-stat = 0.59). The coefficient of determination for this factor is high and equal to 72.35% ($se(\widehat{\mathrm{R}^2_{(6)}}) = 0.138$)[15] and the mean absolute pricing error (MAPE) across all securities is 1.11% per year. A standard deviation increase in exposure to low-frequency uncertainty shocks leads to a decrease in portfolio returns by -2.30% annually. Moreover, the estimated price of risk for the innovations in the seventh uncertainty component is also negative with a t-statistic of -3.21. However the estimated zero-beta excess return for this case is significant at the 1% level (t-stat = 2.37). The performance of the *business-cycle uncertainty* factor (i.e. $\Delta u_t^{(6:7)}$) is similar to $\Delta u_t^{(6)}$ with a cross-sectional R^2 of 73.90% ($se(\widehat{\mathrm{R}^2_{(6:7)}}) = 0.123$) and MAPE equal to 1.11% per year. Finally, for each of the low-frequency factors the Kan et al. (2013) specification test does not reject the hypothesis that the model is correctly specified.

Since $\beta^{(6)} \times \lambda_6 > 0$ (or equivalently $\beta^{(6:7)} \times \lambda_{6:7} > 0$) low-frequency uncertainty shocks carry positive risk premia. My results are in contrast with the work of Campbell et al. (2014) who find that in the post-1963 period equities have positive volatility betas and therefore negative risk premia. However, my findings are in line with Boguth and Kuehn (2013), Bansal, Kiku, Shaliastovich, and Yaron (2014) and Tédongap (2015) who provide evidence of negative exposure of asset returns to alternative measures of volatility risk. In addition, my results are in agreement with Boons and Tamoni (2015) who first show that the price of low-frequency volatility risk is negative and assets

[15]When $0 < \mathrm{R}^2 < 1$, $\widehat{\mathrm{R}^2}$ is asymptotically normally distributed around its true value and thus I cannot use $\widehat{\mathrm{R}^2} \pm 1.96 \times se(\widehat{\mathrm{R}^2})$ to obtain a 95% confidence interval. One way to construct confidence intervals is by pivoting the cumulative distribution function (cdf) (see section 9.2.3 in Casella and Berger, 2002). Kan and Robotti (2009) and Kan and Robotti (2015) use the same method to construct confidence intervals for the Hansen-Jagannathan distance and the Hansen-Jagannathan bound respectively. To preserve space I only report confidence intervals in Table IA.19. The R^2 for the *business-cycle uncertainty* factor is significantly different from zero across all test assets.

have negative low-frequency volatility betas and thus long-run volatility risk premia are positive.

[Insert Figure 3 about here.]

Panel A of Figure 3 plots realized versus fitted average excess returns for the 25 size and book-to-market FF portfolios where the priced factor is $\Delta u_t^{(6:7)}$, that is, the innovations in low-frequency uncertainty shocks (derived from monthly forecasts) with persistence ranging from 32 to 128 months. Each two-digit number represents a separate portfolio. The first digit refers to the size quintile of the portfolio (1 being the smallest and 5 the largest), while the second digit refers to the book-to-market quintile (1 being the lowest and 5 the highest). If the fitted and the realized returns for each portfolio are the same then they should lie on the 45-degree line from the origin. Panel A visually confirms that the fit of the model is good. Similarly, Panel B shows that the factor $\Delta u_t^{(6:7)}$ is successful at explaining the size and value effects.

2.4 Relation with Business-Cycle Indicators and Macroeconomic Volatility Risk

Next, I examine the relation of the low-frequency uncertainty factor $u_t^{(6:7)}$ with macroeconomic variables linked to fluctuations of the business cycle such as the term spread and default spread. It is well-documented that these yield spreads are high around business-cycle troughs and low near peaks (for instance, see Fama and French, 1989; Estrella and Hardouvelis, 1991 and Hahn and Lee, 2006). In addition, the default spread and term spread are known to forecast macroeconomic activity (Boons, 2015) and have long been used as proxies for credit market conditions and the stance of monetary policy, respectively. Following Welch and Goyal (2008), the default spread is defined as the difference between BAA and AAA-rated corporate bond yields. Similarly, the term spread is defined as the difference between the long term yield on government bonds and the three-month Treasury-bill rates. The correlation between the term spread and $u_t^{(6:7)}$ is 0.11 and statistically significant at the 5% level. The correlation between the default spread and $u_t^{(6:7)}$ is 0.48 and statistically significant at the 1% level. That is, an increase in low-frequency aggregate uncertainty is closely associated with the deterioration of credit market conditions.

Moreover, I examine the correlation of $u_t^{(6:7)}$ with the low-frequency macroeconomic volatility risk factor of Boons and Tamoni (2015). To measure macro volatility I consider the following $\text{AR}(1) - \text{GARCH}(1,1)$ specification

$$IPG_t = \mu + \phi IPG_{t-1} + \nu_t, \tag{12}$$

$$\sigma_t^2 = \omega_0 + \omega_1 \nu_{t-1}^2 + \omega_2 \sigma_{t-1}^2 \tag{13}$$

where IPG_t is the (latest vintage) seasonally-adjusted industrial production growth rate from the FRED database of the St. Louis FED and $IPVOL = \widehat{\sigma}_t$. The correlation between uncertainty shocks with persistence between 32 and 128 months (i.e. $u_t^{(6:7)}$) and macro volatility shocks with persistence greater than 32 months (i.e. $IPVOL_t^{(>5)}$) is 0.74 and statistically significant at the 1% level. In other words, there is a close link between long-run uncertainty about the state of the economy and low-frequency variation in the volatility of industrial production. However, the correlation between $\Delta IPVOL_t^{(>5)}$ and innovations in the *business-cycle uncertainty* factor is 0.48 (for $h = 1$) and reduces further to 0.38 (for $h = 12$).

3 Robustness Checks and Additional Tests

3.1 Alternative Test Assets

I confirm that my findings are robust by looking at alternative sets of test portfolios. I use the 25 Fama and French (2015b) size and investment portfolios, the 25 Fama and French (2015b) book-to-market and operating profitability portfolios and the 25 Fama and French (2015a) size and variance portfolios. The initial sample period is 1963:07 to 2013:05. Below I discuss the cross-sectional estimates based on macroeconomic uncertainty derived from monthly forecasts (i.e. $u_t(1)$). The results for aggregate uncertainty derived from quarterly (i.e. $u_t(3)$) and annual (i.e. $u_t(12)$) forecasts are similar.

[Insert Table 5 about here.]

Panel A of Table 5 reports the cross-sectional estimates for the 25 Fama and French (2015b) size and investment portfolios. The estimated price of risk for the innovations in the sixth uncertainty factor is negative (-0.52) with a t-statistic of -3.05 and the estimate of $\hat{\lambda}_{0,6}$ is not significant (t-stat = 1.00). The cross-sectional R^2 is 51.52% ($se(\widehat{\mathrm{R}^2_{(6)}}) = 0.286$) and the MAPE across all securities is less than 1% per year. The pricing performance of the *business-cycle uncertaint*y factor is considerably better among these test portfolios with a cross-sectional R^2 of 73.00% and the lowest sampling variability (i.e. $se(\widehat{\mathrm{R}^2_{(6:7)}}) = 0.092$). In addition, the null hypothesis that the model is correctly specified is not rejected. The price of risk per unit of cross-sectional standard deviation in $\Delta u_t^{(6:7)}$ is -2.21%.

Panel B of Table 5 presents the cross-sectional estimates for the 25 Fama and French (2015b) book-to-market and operating profitability portfolios. The estimated price of risk for $\Delta u_t^{(6)}$ is -0.48 with a t-statistic of -2.98 and the estimated zero-beta excess return is not significant (t-stat = 1.03). The cross-sectional R^2 is 39.20% ($se(\widehat{\mathrm{R}^2_{(6)}}) = 0.177$) and the MAPE across all assets is 2.14% annually. Furthermore, the estimated price of risk for $\Delta u_t^{(6:7)}$ is also significant (t-stat = -3.35) with a similar sample R^2 but smaller standard error ($se(\widehat{\mathrm{R}^2_{(6:7)}}) = 0.142$). The price of risk per unit of cross-sectional standard deviation in $\Delta u_t^{(6:7)}$ is -2.32%. It is worth emphasizing that for all scales the specification test rejects the hypothesis of a perfect fit.

Panel C of Table 5 provides the results from the cross-sectional regressions for the 25 Fama and French (2015a) size and variance portfolios. Low-frequency uncertainty with persistence between 32 and 64 months carries a negative price of risk of -0.50 with a t-statistic of -2.92 and the intercept is insignificant (t-stat = 0.85). The coefficient of determination is equal to 20.60% but is not significantly different from zero ($se(\widehat{\mathrm{R}^2_{(6)}}) = 0.190$). That is, using only the sample R^2 I cannot reject that the factor $\Delta u_t^{(6)}$ has essentially no explanatory power. In contrast, the cross-sectional R^2 for the *business-cycle uncertainty* factor is 54.84% ($se(\widehat{\mathrm{R}^2_{(6:7)}}) = 0.164$) and the null that the model is correctly specified is not rejected.

3.2 Benchmark Results & Controlling for Fama-French Factors

Furthermore, I present in Table 6 benchmark results for the Fama and French (1993) three-factor model (FF3) and the Fama and French (2015b) five-factor model (FF5). The *business-cycle uncertainty* factor performs better than the Fama-French models in the cross-sections of the size and book-to-market and the size and investment portfolios. In particular, while the estimates of the cross-sectional R^2's are similar, the pricing performance of the FF3 and the FF5 model is driven by a statistical significant zero-beta excess return. In addition, both models are misspecified (i.e. the Kan et al., 2013 specification test of $H_0: R^2 = 1$ is strongly rejected). In contrast, the FF5 model explains significantly better the cross-sectional differences of assets sorted across book-to-market and operating profitability. Also, for these test assets the uncertainty factor does not survive in the presence of the profitability-based factor[16]. This finding is in line with Wang and Yu (2015) who demonstrate that the profitability premium (see Novy-Marx, 2013 and Hou et al., 2015) is not driven by macroeconomic risk.

[Insert Table 6 about here.]

3.3 Predictability of Aggregate Returns

Finally, I test the ability of the horizon-dependent shocks filtered out of the index of macroeconomic uncertainty to predict the components of aggregate stock returns with the same time-scale with the following set of regressions

$$r_{t+2^j}^{e(j)} = \beta_0^{(j)} + \beta^{(j)} u_t^{(j)} + \varepsilon_{t+2^j}^{(j)} \quad \text{for } j = 1, \ldots, 7 \tag{14}$$

where $r_t^{e(j)}$ denotes the components of market excess returns associated with scale j at time t and $\varepsilon_{t+2^j}^{(j)}$ are scale-specific forecast errors. The lag between the regressand and the regressor means that fluctuations of time-scale j forecast the next cycle of length 2^j periods. In addition, since scale-wise predictability implies predictability upon two-way (forward for the regressand, backward for the regressor) adaptive aggregation of the series (see the novel work of Bandi et al., 2015) I run the

[16] To preserve space I report the results in the Internet Appendix (see Table IA.10).

following regression

$$r^e_{t+1,t+q} = a_q + \beta_q u_{t-q+1,t} + \eta_{t+q} \tag{15}$$

where $r^e_{t+1,t+q} = \sum_{i=1}^{q} r^e_{t+i}$ denotes excess market returns between $t+1$ and $t+q$ and $u_{t-q+1,t} = \sum_{i=1}^{q} u_{t-i+1}$ past uncertainty. The regressor and regressand are aggregated over non-overlapping periods. Also, the regressor is adapted to time t information and therefore is non anticipative. The reason for aggregating both the regressand and the regressor in Equation (15) resides in the intuition of Bandi and Perron (2008) according to which economic relations may impact highly persistent components of the variables while being hidden by short term noise.

[Insert Table 7 about here.]

Panel A of Table 7 presents the results for the component-wise equity risk premium predictability[17]. I use Newey-West (1987) HAC standard errors with $2^j - 1$ lags and the Hansen-Hodrick (1980) estimator. The coefficient for the uncertainty component with degree of persistence $j = 6$ (i.e. the component that captures fluctuations in uncertainty between 32 and 64 months) is positive and statistical significant at the 1% level with a NW corrected t-statistic of 3.84 and a HH t-statistic of 3.45. For levels of persistence $j = 1, \ldots, 5$ and for $j = 7$ the uncertainty coefficients are insignificant. Due to the initialization of the filtering procedure and the lag between regressor and regressand the effective sample for $j = 7$ is reduced substantially and therefore the statistical inferences are based on a smaller period.

Panel B of Table 7 shows the results from the long-horizon predictive regression. I rely on Newey-

[17] For reviews of the literature on stock return predictability see Welch and Goyal (2008), Cochrane (2008) and more recently Lettau and Ludvigson (2010). For arguments against the validity of standard econometric inference and the statistical pitfalls in long-run predictive regressions in finance see Ferson et al. (2003), Valkanov (2003), Lewellen (2004), Campbell and Yogo (2006) and Boudoukh et al. (2008).

West (1987) corrected t-statistics with $2 \times (q-1)$ lags to correct for serial correlation induced by the overlapping nature of the data. Also, to address any potential inferential problems that arise in predictive regressions with persistent regressors (for instance, see Ferson et al., 2003) I report Valkanov's (2003) rescaled test statistic[18]. In line with the framework of Bandi et al. (2015) aggregation begins to reveal predictability over a horizon between 32 and 64 months (i.e. scale-wise predictability applies for $j = 6$ and therefore $2^{6-1} = 32$ and $2^6 = 64$). Moreover, the slope of the forward/backward regression for a horizon equal to 64 months (i.e. $\beta_{q=64} = 2.81$) is numerically very close to the slope of the relevant scale-wise predictive regression (i.e. $\beta^{(j=6)} = 3.06$). However, dependence increases in the long-run and the R^2 for a horizon of 128 months is around 66%. In addition, there is a rough tent-shaped behavior in the predictive slopes and R^2's. These results indicate that uncertainty shocks with persistence between 64 and 128 months are also positive correlated with future aggregate returns (i.e. if scale-wise predictability was present only for $j = 6$, the maximum R^2 would be achieved for a level of aggregation corresponding to $2^6 = 64$ months). My findings are in line with Bandi and Perron (2008) who report that future excess market returns and past market variance are positively correlated in the long-run (i.e., between 6 and 10 years). Similarly, I confirm the results of Bandi et al. (2015) who document a scale-specific risk-return trade-off in market returns, that is, shocks in consumption and market variance with persistence between 8 and 16 years forecast positively future excess market returns with the same periodicity.

Overall, I demonstrate that business-cycle macroeconomic uncertainty as a risk factor does not meet the restrictions proposed by Maio and Santa-Clara (2012) that prevent ICAPM from being a "fishing license" for researchers. Specifically, the price of risk for exposure to business-cycle variation

[18] For the right-tail critical values of $t/\sqrt{T}$ at various percentiles see the Internet Appendix (Table IA.16).

in aggregate uncertainty is negative and thus inconsistent[19] with how these shocks forecast aggregate returns in the time-series. For instance, consider the cross-section with the 25 FF size and book-to-market portfolios. The intertemporal hedging demand argument implies that the portfolio with the least negative covariance with low-frequency uncertainty (i.e. the portfolio of small firms with small book-to-market values - 11 in Figure 3) will be the least attractive as hedge and thus offer the highest expected return. In contrast, the portfolio with the highest expected return is the one with the most negative exposure (i.e. the portfolio of small firms with high book-to-market values - 15 in Figure 3).

To understand this point further, assume a candidate state variable z_t and consider a discrete-time approximation of the ICAPM in an unconditional form (see Maio and Santa-Clara, 2012)

$$E\left(R_t^{e,i}\right) \approx \gamma Cov\left(R_t^i, R_{m,t}\right) + \gamma_z Cov\left(R_t^i, \Delta z_t\right) \tag{16}$$

where the first term on the right-hand side captures the market risk premium associated with the CAPM, Δz_t denotes the innovations in the variable and γ_z is the covariance risk premium associated with the candidate state variable. Assume that the state variable z_t is positively correlated with future aggregate returns i.e. $Cov\left(z_t, R_{m,t+1}\right) > 0$. Also, that the return on asset i is negatively correlated with the (innovation in the) variable (i.e., $Cov\left(R_t^i, \Delta z_t\right) < 0$) and thus negatively correlated with future aggregate returns. If the risk price γ_z is negative it holds that $\gamma_z Cov\left(R_t^i, \Delta z_t\right) > 0$. That is, even though the asset provides a hedge for reinvestment risk it earns a higher risk premium

[19] I am indebted to Martijn Boons for pointing out this inconsistency in an earlier version of this draft.

than an asset with $Cov\left(R_t^i, \Delta z_t\right) = 0$. The price of risk for z_t is inconsistent with the ICAPM. Thus, in contrast with the interpretation of Bali et al. (2014) and Bali et al. (2015) my results suggest that macro uncertainty is not a valid risk factor under the ICAPM. The central difference is that Bali et al. (2015) assume that "*an increase in economic uncertainty reduces future investment and consumption opportunities*" while my results document a long-run risk-return trade-off (i.e. future aggregate returns are positively correlated with past uncertainty).

3.4 Robustness Checks

In the Internet Appendix I provide a battery of robustness checks. A brief summary is available here. Tables IA.1 through IA.4 present the estimates from the cross-sectional regressions using the same burn-in period for all components. The results for all test assets remain quantitatively similar. In addition, the model with the *business-cycle uncertainty* factor is correctly specified in the joint cross-section of the 5 industry portfolios and the 25 size and book-to-market portfolios (see Table IA.9). The uncertainty factor $u_t^{(6:7)}$ remains statistically significant after controlling for the Fama-French factors (see Table IA.10) and for exposure to momentum, short-term reversal, long-term reversal, liquidity and portfolio characteristics (see Tables IA.11a and IA.11b). Also, the results for the uncertainty factor are similar if I estimate the innovations as the residuals from an AR(1) model fitted to the factor (see Table IA.12). Finally, I present bootstrapped confidence intervals for the first-pass horizon-dependent betas (see Table IA.13), the second-pass cross-sectional estimates (see Table IA.14) and the scale-wise predictive regressions (see Table IA.15) using the bias-corrected percentile method and the stationary bootstrap of Politis and Romano (1994).

4 Monotonicity in Horizon-Specific Risk Exposures

In this section, I examine whether the horizon-specific risk exposures with respect to the factors $\Delta u_t^{(6)}$ and $\Delta u_t^{(6:7)}$ are monotonically increasing (or decreasing) across portfolios using the monotonic relation (MR) test of Patton and Timmermann (2010). In essence, I look for monotonic patterns in the scale-wise factor loadings that match known patterns in average excess returns for portfolios sorted on various firm characteristics. The MR test is nonparametric and is easily implemented via bootstrap methods. To preserve the dependence in the original time-series I use the stationary bootstrap of Politis and Romano (1994) where observations are drawn in blocks whose starting point and length are both random. The block length is drawn from a geometric distribution where the average block size is set equal to 27[20]. For all MR tests I use 5,000 bootstrap replications. Following Patton and Timmermann (2010) and in line with Hansen (2005) and Romano and Wolf (2005) I implement a studentized version of the bootstrap. The MR test is designed so that the alternative hypothesis is the one that the researcher hopes to prove - hence a monotonic relation is confirmed only if there is sufficient evidence in the data to reject the null (for more information see Appendix A).

[Insert Tables 8a and 8b about here.]

Tables 8a and 8b present the horizon-specific risk exposures for one-way portfolio sorts and the corresponding monotonicity tests. I consider average excess returns on a range of portfolios sorted on security characteristics such as size (Panel A), long-term reversal (Panel B), short-term

[20] Calculated based on the Politis and White (2004) estimator of the optimal average block length. Note that the estimator is corrected to deal with the error in Lahiri's (1999) calculation of the variance for the stationary bootstrap - see also Nordman (2009) and Patton et al. (2009).

reversal (Panel C), book-to-market (Panel D), investment (Panel E) and dividend yield (Panel F). The first row in each panel reports average returns (in percent per month) for the test assets. The final column in each panel presents the p-value for the monotonic relation (MR) test. Similarly, the penultimate column presents the bootstrap p-value for the top-minus-bottom difference in the corresponding returns and scale-wise betas.

Panel A of Table 8a shows that the MR test rejects the null of a flat or weakly decreasing pattern across size in the risk loadings with respect to the factor $\Delta u_t^{(6)}$ for $h = 1, 3$ at the 10% level. Similarly, the evidence in Panel E of Table 8b provide strong support for a monotonically increasing relation in the horizon-dependent risk exposures across investment. In particular, the MR test detects a monotonically increasing pattern which is significant at the 1% level for the risk exposures to the factor $\Delta u_t^{(6)}$ and at the 5% level for the risk exposures to $\Delta u_t^{(6:7)}$. Given that all risk loadings are negative these results mean that an increase in low-frequency uncertainty has a smaller effect on large firms and aggressive firms. Hence, consistent with the size and the investment effects these securities offer smaller risk compensations.

In addition, there is statistically significant evidence at the 10% level for a monotonically decreasing relation in the horizon-specific risk loadings across book-to-market. This finding is in line with the value effect (i.e. one-period average returns increase from growth to value stocks). Also, it is consistent with the work of Hansen et al. (2008) who show that cash flows from value portfolios[21] are positively correlated with long-run shocks in the economy while cash flows from growth portfolios are not and hence investors holding value portfolios must be compensated for bearing the extra risk.

[21] In a similar fashion, Kamara et al. (2015) find that the risk price for exposure to the HML factor of Fama and French (1993) (i.e. the factor that measures the difference between the returns on portfolios of high and low book-to-market stocks) peaks at a horizon of two to three years.

Moreover, low-frequency uncertainty betas decrease monotonically across stocks sorted on dividend yield (the null is strongly rejected at the 1% level). Overall, these findings provide a clear economic explanation for the well-documented size, value, dividend-yield and investment effects based on exposures to low-frequency macro uncertainty. Finally, there is significant evidence for an increasing pattern in the risk exposures of securities sorted across long-term and short-term reversal. That is, the top-minus-bottom difference in the corresponding scale-wise betas is statistically significant at the 5% level with respect to all factors.

5 Conclusions

I study how the pricing of macroeconomic uncertainty varies across investment horizons. In particular, I decompose aggregate uncertainty into heterogeneous - in terms of their persistence and periodicity - components and investigate the risk compensations associated with each of these horizon-dependent macroeconomic shocks. Macroeconomic uncertainty is quantified using the model-free index of Jurado et al. (2015) that measures the common variation in the unforecastable component of a large number of economic indicators. My study is based on the novel framework for scale-specific analysis of risk proposed in Bandi and Tamoni (2015) and Boons and Tamoni (2015).

I document that a single *business-cycle uncertainty* factor that captures assets' exposure to low-frequency variation in macroeconomic uncertainty can explain the level and the cross-sectional differences of asset returns. In particular, I find that macroeconomic fluctuations with persistence levels ranging from 32 to 128 months carry a negative price of risk about -2% annually. In addition, equity horizon-specific risk exposures are negative and thus uncertainty risk premia are positive.

The results are robust across different test assets including: the 25 Fama and French (1993) size and book-to-market portfolios, the 25 Fama and French (2015b) size and investment portfolios, the 25 Fama and French (2015b) book-to-market and operating profitability portfolios and the 25 Fama and French (2015a) size and variance portfolios. Moreover, my findings remain statistically significant after using a t-statistic cutoff of three as suggested by Harvey et al. (2016) and are qualitatively and quantitatively similar irrespective of whether uncertainty is derived from monthly, quarterly or annual forecasts. Furthermore, unlike several prominent asset pricing models (e.g. FF3 and FF5) I demonstrate that the one-factor model with business-cycle macro uncertainty is correctly specified. In total, my study suggests that only business-cycle variation in uncertainty drives asset prices and hence provides useful insights for the long-run risks literature. That is, in the spirit of Dew-Becker and Giglio (2015) we should allow Epstein-Zin preferences to put more weight on business-cycle frequency fluctuations compared to the standard Bansal and Yaron (2004) calibration (for instance, see Ghosh and Constantinides, 2014).

Finally, I show that future excess aggregate returns are positively correlated with past uncertainty and thus the negative price of risk for exposure to (low-frequency) macro uncertainty is inconsistent with the central economic intuition underlying the ICAPM. In contrast, investors demand higher risk compensations to hold portfolios that exhibit greater negative comovement with low-frequency macroeconomic uncertainty, i.e. there is a low-frequency risk-return trade-off for the valuation of assets. Future research can expand my work in the cross-section of hedge fund and mutual fund returns.

Appendix A: Monotonicity in Factor Loadings

I present how to implement the monotonic relation (MR) test of Patton and Timmermann (2010) to test for monotonicity in factor loadings. The MR test specifies a flat or weakly pattern under the null hypothesis and a strictly monotonic relation under the alternative[22]. The main advantage of the test is that it makes no parametric assumptions on the distribution from which the data are drawn. In this section I describe the MR methodology for the general case with the extension for horizon-specific exposures being straightforward (i.e. component-wise regressions as in Equation (9)).

Let $\{r_{i,t},\ i = 1, \ldots, N; t = 1, \ldots, T\}$ be the set of returns recorded for N assets over T time periods which is regressed on K risk factors $\boldsymbol{F}_t = (F_{1,t}, \ldots, F_{K,t})^{'}$, that is,

$$r_{i,t} = \boldsymbol{\beta}_i \boldsymbol{F}_t + e_{i,t} \tag{A.1}$$

where $\boldsymbol{\beta}_i = (\beta_{1,i}, \ldots, \beta_{K,i})$. The associated hypotheses on the $j - th$ parameter $(1 \leq j \leq K)$ in the above regression is

$$H_0: \ \beta_{j,N} \leq \beta_{j,N-1} \leq \ldots \leq \beta_{j,1} \text{ versus} \tag{A.2}$$

$$H_1: \ \beta_{j,N} > \beta_{j,N-1} > \ldots > \beta_{j,1}. \tag{A.3}$$

The alternative hypotheses can be rewritten as

[22] To test for monotonically decreasing patters the order of the assets is simply reserved.

$$H_1: \min_{i=1,\ldots,N} \{\beta_{j,i} - \beta_{j,i-1}\} > 0 \tag{A.4}$$

that is if the smallest value of $\{\beta_{j,i} - \beta_{j,i-1}\} > 0$ then it must be that $\{\beta_{j,i} - \beta_{j,i-1}\} > 0$ for all $i = 1, \ldots, N$.

Patton and Timmermann (2010) use the stationary bootstrap of Politis and Romano (1994) to randomly draw a new sample of returns and factors $\left\{\tilde{r}^{(b)}_{i,\tau(t)},\ i = 1, \ldots, N; \tau(1), \ldots, \tau(T)\right\}$ and $\left\{\boldsymbol{F}^{(b)}_{\tau(t)},\ \tau(1), \ldots, \tau(T)\right\}$ where $\tau(t)$ is the new time index which is a random draw from the original set $\{1, \ldots, T\}$ and b is an indicator for the bootstrap number which runs from $b = 1$ to $b = B$. To preserve any cross-sectional dependencies in returns the randomized time index $\tau(t)$ is common across portfolios. Moreover, observations are re-sampled in blocks - to preserve the dependence in the original series - where the size of each block is random and determined by a geometric distribution. The bootstrap regression takes the form

$$\tilde{r}^{(b)}_{i,\tau(t)} = \boldsymbol{\beta}^{(b)}_i \boldsymbol{F}^{(b)}_{\tau(t)} + e^{(b)}_{i,\tau(t)}. \tag{A.5}$$

The null hypothesis is imposed by subtracting the estimated parameter $\hat{\boldsymbol{\beta}}_i$ from the parameter estimate obtained on the bootstrapped series $\hat{\boldsymbol{\beta}}^{(b)}_i$. The test statistic for the bootstrap sample - motivated by Equation (A.4) - is computed as

$$J^{(b)}_{j,T} \equiv \min_{i=1,\ldots,N} \left\{ \left(\hat{\beta}^{(b)}_{j,i} - \hat{\beta}_{j,i}\right) - \left(\hat{\beta}^{(b)}_{j,i-1} - \hat{\beta}_{j,i-1}\right) \right\}. \tag{A.6}$$

Patton and Timmermann (2010) then count the number of times a pattern at least as unfavorable against the null as that observed in the real sample emerges. An estimate of the p-value for the null hypothesis is given by

$$\hat{p} = \frac{1}{B} \sum_{b=1}^{B} \mathbf{1} \left\{ J_{j,T}^{(b)} > J_{j,T} \right\} \tag{A.7}$$

where the indicator $\mathbf{1}\left\{J_{j,T}^{(b)} > J_{j,T}\right\}$ is one if $J_{j,T}^{(b)} > J_{j,T}$ and otherwise zero. When the bootstrap p-value is less than 0.05 there are significant evidence against the null in favor of a monotonically increasing relation. To eliminate the impact of cross-sectional heteroskedasticity Patton and Timmermann (2010) suggest implementing a studentized version of the bootstrap in line with Hansen (2005) and Romano and Wolf (2005).

Appendix B: Additional Results

Table B.1: Cross-sectional regressions using the raw series of aggregate uncertainty

Panel A	25 FF size and book-to-market						
	λ_0		λ_u		R^2	$p\left(R^2=0\right)$	MAPE
$u_t\,(1)$	0.6038	(2.0306)	-0.1844	(-0.3039)	0.52%	0.8580	2.12%
$u_t\,(3)$	0.6091	(2.0568)	-0.1251	(-0.2883)	0.55%	0.8343	2.12%
$u_t\,(12)$	0.3370	(1.2950)	-0.2794	(-1.1998)	7.68%	0.5173	1.95%
Panel B	**25 FF size and investment**						
	λ_0		λ_u		R^2	$p\left(R^2=0\right)$	MAPE
$u_t\,(1)$	0.7411	(3.3525)	0.0398	(0.0828)	0.04%	0.9548	2.09%
$u_t\,(3)$	0.5821	(2.2972)	-0.1497	(-0.3915)	1.10%	0.7443	2.04%
$u_t\,(12)$	0.3729	(1.4918)	-0.2089	(-1.0464)	7.62%	0.4250	1.91%
Panel C	**25 FF book-to-market and operating profitability**						
	λ_0		λ_u		R^2	$p\left(R^2=0\right)$	MAPE
$u_t\,(1)$	0.4466	(1.9274)	-0.2766	(-0.6264)	0.80%	0.8515	2.72%
$u_t\,(3)$	0.7573	(3.1434)	0.1737	(0.5037)	0.66%	0.8285	2.73%
$u_t\,(12)$	0.3585	(1.6464)	-0.1667	(-1.0829)	2.76%	0.6558	2.69%
Panel D	**25 FF size and variance**						
	λ_0		λ_u		R^2	$p\left(R^2=0\right)$	MAPE
$u_t\,(1)$	0.8117	(3.9496)	0.1809	(0.3826)	1.04%	0.7324	2.97%
$u_t\,(3)$	0.7505	(3.7272)	0.0635	(0.1896)	0.26%	0.8617	2.95%
$u_t\,(12)$	0.5941	(3.0081)	-0.0560	(-0.3189)	0.66%	0.8042	2.86%

Notes: This table reports the estimates for the zero-beta excess return (λ_0) and the price of risk (λ_u) for the innovations in the raw series of aggregate uncertainty along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. The innovations are the residuals from an AR (1) model fitted to the factor. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D). In addition, I report the sample R^2 for each cross-sectional regression, the p-value for the Kan et al. (2013) test of $H_0: R^2=0$ denoted as $p\left(R^2=0\right)$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year.

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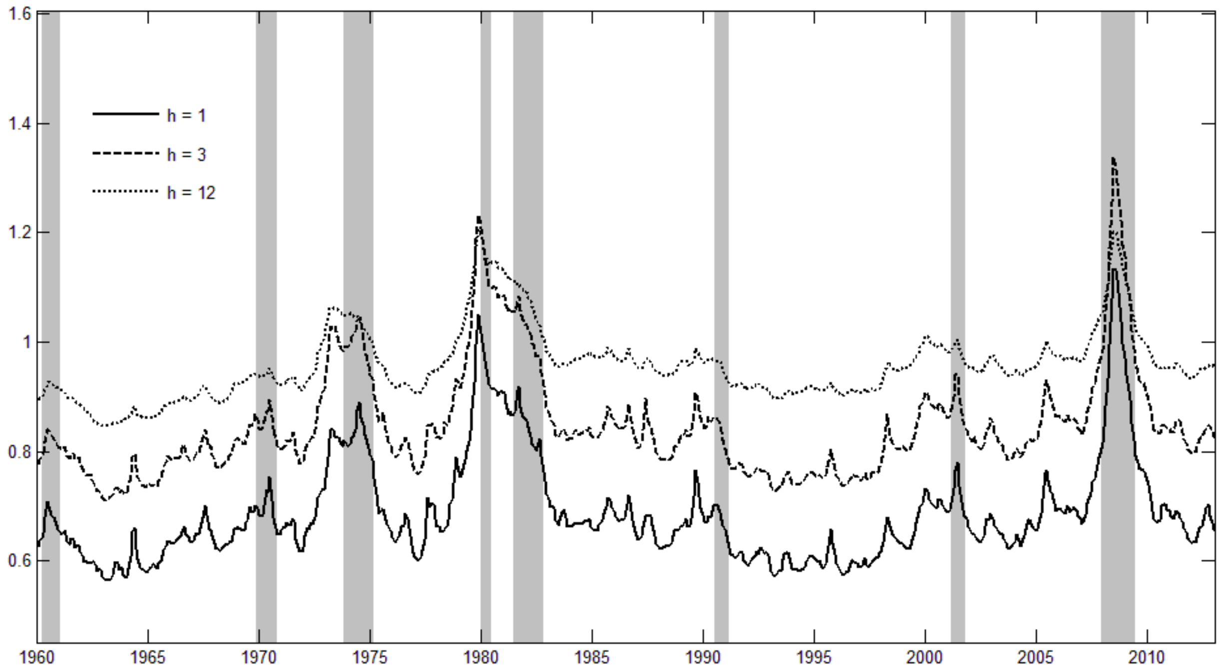
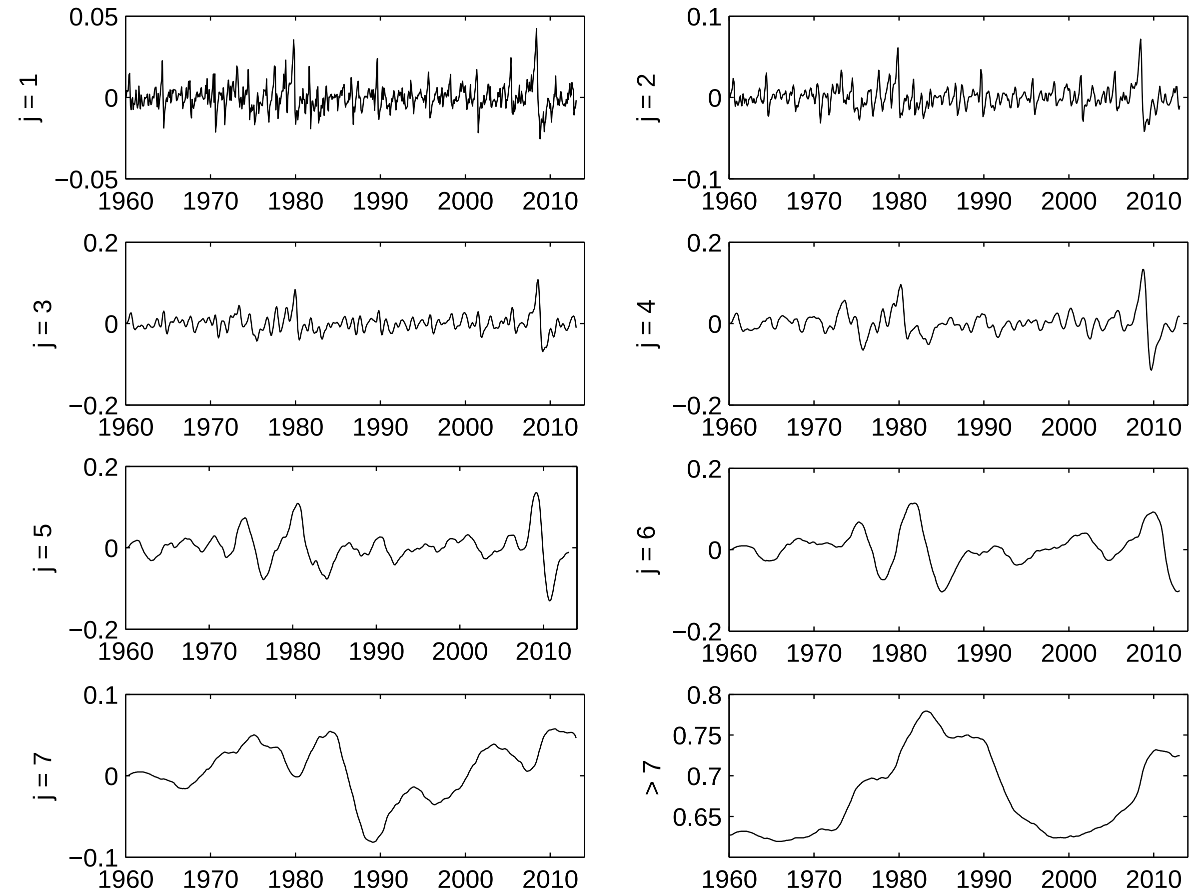
Figure 1: Aggregate uncertainty



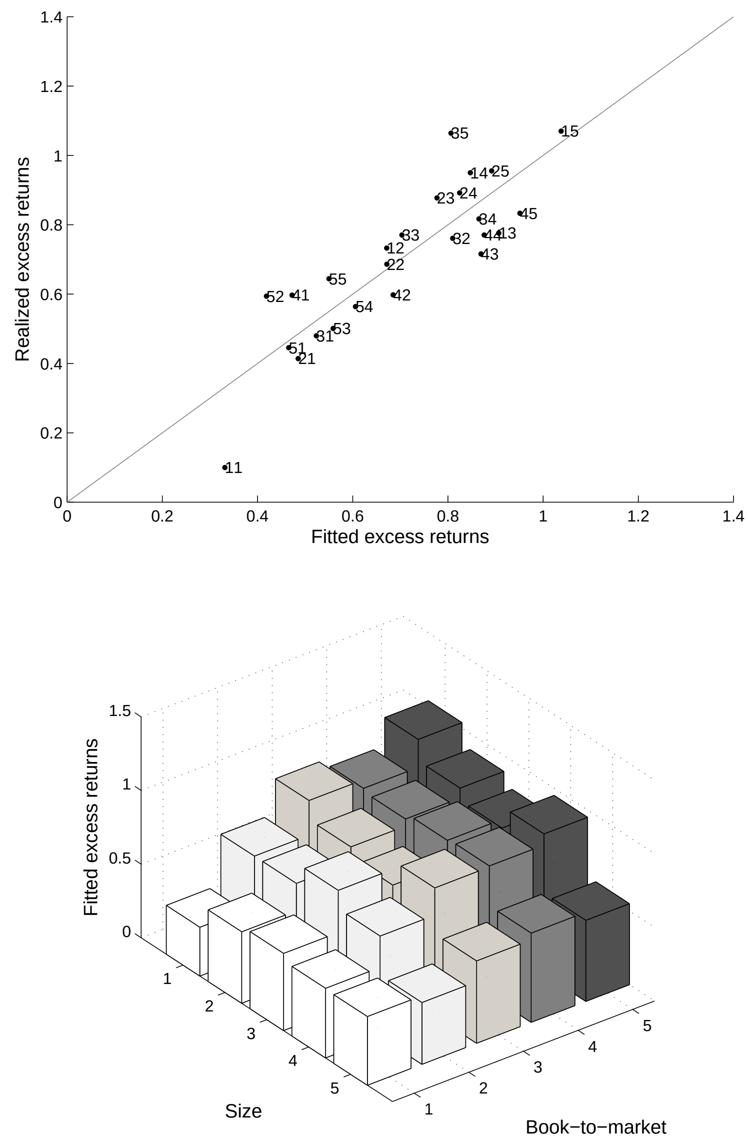
Notes: This figure plots the index of macroeconomic uncertainty of Jurado et al. (2015) for $h = 1, 3, 12$. Data are monthly and span the period 1960:07 - 2013:05. The shaded areas represent NBER recessions.

Figure 2: Persistence-based decomposition of aggregate uncertainty



Notes: This figure plots the persistent components $u_t^{(j)}$ for $j = 1, \ldots, 7, > 7$ filtered out of aggregate uncertainty (derived from monthly forecasts - $h = 1$). Data are monthly and span the period 1960:07 - 2013:05. In the empirical analysis, I discard the first $2^j - 1$ observations for each scale due to the initialization of the filtering procedure.

Figure 3: Cross-sectional fit - 25 FF size and book-to-market portfolios



Notes: Panel A plots realized versus fitted excess returns for the 25 size and book-to-market Fama and French (1993) portfolios where the priced factor is $\Delta u_t^{(6:7)}$, that is, the innovations in low-frequency uncertainty shocks (derived from monthly forecasts) with persistence ranging from 32 to 128 months. Each two-digit number represents a separate portfolio. The first digit refers to the size quintile of the portfolio (1 being the smallest and 5 the largest), while the second digit refers to the book-to-market quintile (1 being the lowest and 5 the highest). The straight line is the 45-degree line from the origin. Panel B plots the fitted excess return for each portfolio.

Table 1: Descriptive statistics and frequency interpretation

Panel A	Aggregate uncertainty		
	$u_t\,(1)$	$u_t\,(3)$	$u_t\,(12)$
Mean	0.6871	0.8494	0.9591
Median	0.6655	0.8263	0.9509
Min	0.5635	0.7105	0.8467
Max	1.1344	1.3385	1.2052
St. Deviation	0.0949	0.1020	0.0668
Skewness	1.8179	1.7791	1.2918
Kurtosis	6.9444	6.7326	4.9931
JB	761.40	703.60	281.70
ADF	0.0057	0.0023	0.0396
PP	0.0190	0.0209	0.0475
KPSS	0.1930	0.2119	0.4043
AC(1)	0.9866	0.9891	0.9943
AC(2)	0.9578	0.9651	0.9811
Panel B	Equity risk premium $r^e \equiv r_m - r_f$		
$E\,(r^e)$	5.71%		
$\sigma\,(r^e)$	15.02%		
# observations	635		
Panel C			
Persistence level	Monthly-frequency resolution		
$j = 1$	1 - 2 months		
$j = 2$	2 - 4 months		
$j = 3$	4 - 8 months		
$j = 4$	8 - 16 months		
$j = 5$	16 - 32 months		
$j = 6$	32 - 64 months		
$j = 7$	64 - 128 months		
$j > 7$	$>$ 128 months		

Notes: Panel A reports descriptive statistics for the model-free index of macroeconomic uncertainty of Jurado et al. (2015) for $h = 1, 3, 12$. I report the sample mean, median, minimum, maximum, standard deviation, skewness and kurtosis. In addition, I report the value of the Jarque-Bera (1980) normality test, the p-values of the Augmented Dickey-Fuller (ADF - Dickey and Fuller, 1979) and Phillips-Perron (PP - Phillips and Perron, 1988) tests for unit root, the values of the KPSS (Kwiatkowski et al., 1992) test statistic for the null hypothesis of stationarity whose critical values are 0.347, 0.463 and 0.739 at the 10%, 5% and 1% significance levels respectively as well as autocorrelation coefficients for the first and second lag. Panel B presents the mean and standard deviation for the equity risk premium. Panel C provides the frequency interpretation of the component $u_t^{(j)}$ at level of persistence j in the case of monthly time series. Each persistence level (or time-scale) is associated with a range of time horizons.

Table 2: Multi-scale variance ratio tests

$u_t\,(1)$	Persistence level						
$j =$	1	2	3	4	5	6	7
$\sqrt{\frac{T}{a_j}}\left(\hat{\xi}_j - \frac{1}{2^j}\right)$	**-15.7837**	**-8.5535**	**-3.9397**	1.4228	**12.0042**	**27.9433**	**29.4710**
$u_t\,(3)$	Persistence level						
$j =$	1	2	3	4	5	6	7
$\sqrt{\frac{T}{a_j}}\left(\hat{\xi}_j - \frac{1}{2^j}\right)$	**-15.8286**	**-8.6762**	**-4.1963**	1.3380	**12.4039**	**29.4475**	**29.9408**
$u_t\,(12)$	Persistence level						
$j =$	1	2	3	4	5	6	7
$\sqrt{\frac{T}{a_j}}\left(\hat{\xi}_j - \frac{1}{2^j}\right)$	**-15.9153**	**-8.9182**	**-4.8236**	0.3004	**11.4487**	**30.3735**	**33.4243**

Notes: This table presents the results of the multi-scale variance ratio test for the macroeconomic uncertainty series. The test statistic is given by

$$\hat{\xi}_j = \frac{2^j \left(\mathbf{u}^{(\mathbf{j})}\right)^\intercal \mathbf{u}^{(\mathbf{j})}}{\left(X_T^{(J)}\right)^\intercal X_T^{(J)}}$$

where $\left(X_T^{(J)}\right)^\intercal = [u_T, u_{T-1}, \ldots, u_1]$ is the vector collecting the observations of $\{u_t\}$ and $\mathbf{u}^{(\mathbf{j})} = \left[u_{2^j}^{(j)}, \ldots, u_{k\times 2^j}^{(j)}, \ldots, u_T^{(j)}\right]^\intercal$. Under the null hypothesis of no serial correlation, the rescaled test statistic $\sqrt{\frac{T}{a_j}}\left(\hat{\xi}_j - \frac{1}{2^j}\right)$ where $a_j = \frac{\binom{2^j}{2}}{2^j 2^{2(j-1)}}$ converges in distribution to a standard normal. Bold values reject the null hypothesis of no serial correlation at a 99% confidence level.

Table 3: Horizon-specific risk exposures: 25 FF size and book-to-market portfolios

Size	Book-to-market	$\beta^{(6)}$		$\beta^{(7)}$		$\beta^{(6:7)}$	
Small	LowBM	-0.5009	(-0.7619)	0.8891	(0.8479)	-0.3286	(-0.4172)
	2BM	-0.8292	(-1.7491)	-0.0996	(-0.1249)	-0.7378	(-1.3476)
	3BM	**-1.1794**	(-3.3176)	-0.4014	(-0.6297)	**-1.0207**	(-2.4147)
	4BM	**-1.0991**	(-3.1857)	-0.5002	(-0.7768)	**-0.9490**	(-2.3937)
	HighBM	**-1.3221**	(-3.5890)	-0.9179	(-1.3207)	**-1.1782**	(-2.8421)
2	LowBM	-0.5355	(-0.8820)	0.7294	(0.9866)	-0.5141	(-0.7595)
	2BM	-0.7527	(-1.8718)	0.0292	(0.0641)	-0.7381	(-1.7754)
	3BM	**-0.8812**	(-3.2527)	-0.6270	(-1.7518)	**-0.8648**	(-3.0858)
	4BM	**-1.0595**	(-3.6246)	-0.6058	(-1.6515)	**-0.9221**	(-3.1867)
	HighBM	**-1.1039**	(-3.8263)	-0.6804	(-1.6239)	**-1.0029**	(-3.4157)
3	LowBM	-0.4551	(-0.9432)	0.2801	(0.6001)	-0.5600	(-1.0819)
	2BM	**-0.9081**	(-2.6138)	-0.3593	(-0.9720)	**-0.9045**	(-2.6204)
	3BM	**-0.7960**	(-3.3909)	-0.4716	(-1.3342)	**-0.7760**	(-3.1721)
	4BM	**-1.0044**	(-3.6011)	**-0.7243**	(-2.2801)	**-0.9707**	(-3.4232)
	HighBM	**-0.9016**	(-3.5585)	**-0.8654**	(-2.3183)	**-0.8999**	(-3.2320)
4	LowBM	-0.3571	(-0.7628)	0.2956	(1.1102)	-0.4984	(-1.0381)
	2BM	-0.7447	(-1.8865)	-0.1957	(-0.5350)	-0.7538	(-1.9587)
	3BM	**-1.0108**	(-2.5861)	**-0.6028**	(-2.1452)	**-0.9759**	(-2.5932)
	4BM	**-1.0327**	(-4.0000)	**-0.6834**	(-2.3251)	**-0.9840**	(-4.0463)
	HighBM	**-1.0733**	(-3.6085)	**-0.8784**	(-3.2126)	**-1.0742**	(-4.0577)
Big	LowBM	-0.3370	(-1.4223)	0.0721	(0.1365)	-0.4900	(-1.8189)
	2BM	-0.4133	(-1.3696)	-0.1998	(-0.6944)	-0.4338	(-1.7910)
	3BM	-0.5888	(-1.7174)	-0.2065	(-0.7524)	-0.6023	(-1.7478)
	4BM	**-0.6579**	(-2.7198)	-0.3567	(-1.0614)	**-0.6590**	(-2.9868)
	HighBM	**-0.5883**	(-3.0566)	-0.5782	(-1.1847)	**-0.5917**	(-3.3996)
	Wald-stat	232.88		34.34		314.71	
	p-value	0.0000		0.1008		0.0000	

Notes: This table reports first-pass beta estimates for the Fama and French (1993) 25 size and book-to-market portfolios (indexed by Small to Big and LowBM to HighBM). The betas are estimated component-wise that is regressing low frequency components of returns on the low frequency components of aggregate uncertainty. The associated t-statistics are based on Newey-West standard errors with $2^j - 1$ lags. The last rows of the table present the Wald test-statistics and their corresponding p-values from testing the joint hypothesis that all component-wise exposures are equal to zero, i.e. $H_0 : \beta^{1(j)} = \ldots = \beta^{25(j)} = 0$ for $j = 6, 7$ and $j = 6:7$. The initial sample period is 1960:07 to 2013:05. Bold values denote statistically significant beta estimates at a 95% confidence level.

Table 4: Cross-sectional regression: 25 FF size and book-to-market portfolios

	Persistence level							
$j =$	1	2	3	4	5	6	7	6:7
$u_t\,(1)$								
$\lambda_{0,j}$	1.1321	0.9394	0.9242	0.3666	0.2484	0.1388	0.5814	0.0581
	(4.2639)	(4.0669)	(4.3238)	(1.7363)	(1.1258)	(0.5814)	(2.3717)	(0.2083)
λ_j	0.9062	0.3927	0.4412	-0.4048	-0.4815	-0.6867	-0.4016	-0.8315
	(1.3752)	(0.8124)	(0.9648)	(-1.3683)	(-1.9901)	(-4.5662)	(-3.2124)	(-4.3264)
price of risk	0.832%	0.534%	0.636%	-0.593%	-1.181%	-2.296%	-2.295%	-2.274%
R^2	9.861%	4.103%	5.734%	4.836%	19.080%	72.350%	75.271%	73.891%
$se(\widehat{\mathrm{R}^2})$	0.1351	0.1034	0.1234	0.0815	0.2037	0.1378	0.2375	0.1224
$p\left(\mathrm{R}^2 = 1\right)$	0.0074	0.0078	0.0087	0.0061	0.0102	0.2412	0.2956	0.3139
MAPE	2.075%	2.191%	2.199%	2.068%	1.818%	1.106%	1.156%	1.114%
$u_t\,(3)$								
$\lambda_{0,j}$	0.8821	0.9203	0.9129	0.3682	0.2189	0.1709	0.5836	0.1109
	(3.6045)	(3.7609)	(4.0607)	(1.4875)	(0.9945)	(0.7260)	(2.4041)	(0.4097)
λ_j	0.1843	0.2041	0.2946	-0.3428	-0.5189	-0.7172	-0.4259	-0.8476
	(0.5834)	(0.6652)	(0.8311)	(-1.0914)	(-2.1283)	(-4.5630)	(-3.3841)	(-4.3044)
price of risk	0.407%	0.455%	0.564%	-0.560%	-1.277%	-2.311%	-2.340%	-2.285%
R^2	2.365%	2.982%	4.507%	4.308%	22.305%	73.295%	78.251%	74.617%
$se(\widehat{\mathrm{R}^2})$	0.0837	0.0915	0.1127	0.0899	0.2204	0.1399	0.2066	0.1311
$p\left(\mathrm{R}^2 = 1\right)$	0.0062	0.0072	0.0080	0.0051	0.0117	0.2526	0.3255	0.3229
MAPE	2.177%	2.177%	2.197%	2.074%	1.758%	1.093%	1.075%	1.079%
$u_t\,(12)$								
$\lambda_{0,j}$	0.8354	0.9365	0.9217	0.2302	0.1801	0.2641	0.6407	0.2278
	(4.1869)	(4.1552)	(4.0731)	(0.9144)	(0.8476)	(1.1221)	(2.6882)	(0.8350)
λ_j	0.0951	0.1150	0.1318	-0.2364	-0.3230	-0.4253	-0.2284	-0.4856
	(0.5941)	(0.8194)	(0.8588)	(-1.5547)	(-2.5357)	(-4.5387)	(-2.9019)	(-4.0302)
price of risk	0.337%	0.561%	0.577%	-0.855%	-1.531%	-2.339%	-2.182%	-2.336%
R^2	1.615%	4.524%	4.709%	10.047%	32.070%	75.103%	68.037%	77.922%
$se(\widehat{\mathrm{R}^2})$	0.0564	0.1135	0.1139	0.1446	0.2591	0.1226	0.2665	0.1147
$p\left(\mathrm{R}^2 = 1\right)$	0.0037	0.0082	0.0083	0.0059	0.0187	0.2766	0.1920	0.3653
MAPE	2.192%	2.175%	2.187%	1.963%	1.608%	1.069%	1.315%	1.029%
# observ.	633	631	627	619	603	571	507	507

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,j}$) and the price of risk (λ_j) for each scale j along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I normalize the scale-wise risk exposures and estimate the price of risk per unit of cross-sectional standard deviation in exposure in percent per year. I also report the sample R^2 for each cross-sectional regression and its standard error, the p-value for the Kan et al. (2013) test of $H_0: R^2 = 1$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year.

Table 5: Cross-sectional regressions: Additional test assets

Panel A	25 FF size and investment								
	$\lambda_{0,j}$		λ_j		price of risk	R^2	$se(\widehat{R^2})$	$p\,(R^2=1)$	MAPE
$\Delta u_t^{(6)}$, $h=1$	0.2322	(1.0019)	-0.5147	(-3.0417)	-1.757%	51.221%	0.2858	0.0529	0.924%
$\Delta u_t^{(6)}$, $h=3$	0.2605	(1.1360)	-0.5338	(-3.0814)	-1.775%	52.221%	0.2854	0.0565	0.915%
$\Delta u_t^{(6)}$, $h=12$	0.3194	(1.3954)	-0.3290	(-3.3864)	-1.867%	57.812%	0.2693	0.0843	0.849%
$\Delta u_t^{(6:7)}$, $h=1$	0.1923	(0.6872)	-0.8591	(-4.6799)	-2.212%	73.006%	0.0922	0.2508	0.985%
$\Delta u_t^{(6:7)}$, $h=3$	0.2531	(0.9309)	-0.8672	(-4.6254)	-2.227%	74.027%	0.0934	0.2645	0.963%
$\Delta u_t^{(6:7)}$, $h=12$	0.4021	(1.4791)	-0.4750	(-4.5760)	-2.166%	70.012%	0.1424	0.2089	1.078%
Panel B	**25 FF book-to-market and operating profitability**								
	$\lambda_{0,j}$		λ_j		price of risk	R^2	$se(\widehat{R^2})$	$p\,(R^2=1)$	MAPE
$\Delta u_t^{(6)}$, $h=1$	0.2438	(1.0298)	-0.4761	(-2.9832)	-2.101%	39.193%	0.1769	0.0236	2.140%
$\Delta u_t^{(6)}$, $h=3$	0.2632	(1.1230)	-0.5065	(-2.9861)	-2.120%	39.899%	0.1784	0.0229	2.138%
$\Delta u_t^{(6)}$, $h=12$	0.3190	(1.3921)	-0.3100	(-3.0097)	-2.179%	42.155%	0.1781	0.0231	2.116%
$\Delta u_t^{(6:7)}$, $h=1$	0.2989	(1.1748)	-0.6375	(-3.3535)	-2.322%	39.300%	0.1418	0.0151	2.231%
$\Delta u_t^{(6:7)}$, $h=3$	0.3255	(1.2899)	-0.6781	(-3.3478)	-2.376%	41.156%	0.1465	0.0137	2.190%
$\Delta u_t^{(6:7)}$, $h=12$	0.3887	(1.5558)	-0.4199	(-3.3174)	-2.499%	45.510%	0.1547	0.0110	2.083%
Panel C	**25 FF size and variance**								
	$\lambda_{0,j}$		λ_j		price of risk	R^2	$se(\widehat{R^2})$	$p\,(R^2=1)$	MAPE
$\Delta u_t^{(6)}$, $h=1$	0.1962	(0.8494)	-0.5079	(-2.9246)	-1.809%	20.607%	0.1898	0.0072	2.371%
$\Delta u_t^{(6)}$, $h=3$	0.2171	(0.9437)	-0.5390	(-2.9948)	-1.844%	21.427%	0.1928	0.0079	2.342%
$\Delta u_t^{(6)}$, $h=12$	0.2404	(0.9901)	-0.3763	(-3.5909)	-2.120%	28.315%	0.2013	0.0110	2.227%
$\Delta u_t^{(6:7)}$, $h=1$	-0.1131	(-0.3569)	-1.2460	(-5.3519)	-2.908%	54.840%	0.1644	0.0721	1.827%
$\Delta u_t^{(6:7)}$, $h=3$	-0.0194	(-0.0624)	-1.2545	(-5.1685)	-2.918%	55.231%	0.1699	0.0711	1.832%
$\Delta u_t^{(6:7)}$, $h=12$	0.1788	(0.5214)	-0.7293	(-4.0420)	-3.067%	61.006%	0.1278	0.0694	1.775%

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,j}$) and the price of risk (λ_j) for the factors $\Delta u_t^{(6)}$ and $\Delta u_t^{(6:7)}$ where $h = 1, 3, 12$ along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I normalize the scale-wise risk exposures and estimate the price of risk per unit of cross-sectional standard deviation in exposure in percent per year. Also, I report the sample R^2 for each cross-sectional regression and its standard error, the p-value for the Kan et al. (2013) test of $H_0: R^2 = 1$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year. The test assets include: the 25 FF size and investment portfolios (Panel A), the 25 FF book-to-market and operating profitability portfolios (Panel B) and the 25 FF size and variance portfolios (Panel C). The initial sample period is 1963:07 to 2013:05 (for $j = 6$ # observ.=536 and for $j = 6:7$ # observ.=472).

Table 6: Benchmark results

	λ_0	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	$\frac{R^2}{\widehat{se(R^2)}}$	$p\left(R^2 = 1\right)$
Panel A	25 FF size and book-to-market							
FF3	1.1103	-0.5860	0.1778	0.4138	-	-	66.560%	0.0001
	(3.7619)	(-1.6140)	(1.2666)	(3.0169)			0.1460	
	[3.3791]	[-1.4863]	[1.2722]	[3.0206]				
FF5	0.9421	-0.4611	0.2564	0.3687	0.5107	-0.0142	77.950%	0.0007
	(3.1163)	(-1.2548)	(1.8439)	(2.6944)	(2.7784)	(-0.0575)	0.1084	
	[2.5523]	[-1.0863]	[1.8403]	[2.5476]	[2.2142]	[-0.0359]		
Panel B	25 FF size and investment							
FF3	0.9590	-0.3379	0.2109	0.6055	-	-	74.415%	0.0023
	(3.2698)	(-0.9306)	(1.4811)	(3.3346)			0.1099	
	[2.7528]	[-0.8470]	[1.4717]	[3.1248]				
FF5	0.8245	-0.2109	0.2407	0.3824	0.1107	0.3576	75.834%	0.0004
	(2.4468)	(-0.5328)	(1.6776)	(1.6740)	(0.5787)	(3.6348)	0.1091	
	[1.9450]	[-0.4484]	[1.5803]	[1.2581]	[0.4088]	[3.5325]		
Panel C	25 FF book-to-market and operating profitability							
FF3	0.1686	0.3696	0.0247	0.5255	-	-	71.126%	0.0106
	(0.3580)	(0.7267)	(0.0874)	(3.3733)			0.1405	
	[0.2695]	[0.5638]	[0.0679]	[3.3014]				
FF5	0.7580	-0.2738	1.0895	0.2237	0.5063	-0.0583	93.405%	0.9534
	(1.4494)	(-0.4985)	(2.7552)	(1.4268)	(3.5418)	(-0.2933)	0.0532	
	[1.1686]	[-0.4125]	[2.2228]	[1.3061]	[2.9390]	[-0.2426]		
Panel D	25 FF size and variance							
FF3	0.1980	0.3438	-0.0091	0.9930	-	-	47.852%	0.0000
	(1.1010)	(1.2297)	(-0.0568)	(4.1240)			0.1593	
	[0.7195]	[1.0642]	[-0.0596]	[3.5421]				
FF5	1.1941	-0.5890	0.2995	-0.7029	1.4874	-1.6425	86.040%	0.0792
	(6.2037)	(-2.0752)	(1.9802)	(-2.4626)	(7.3199)	(-5.9008)	0.0644	
	[3.2846]	[-1.4610]	[1.7875]	[-1.4275]	[4.1041]	[-3.1551]		

Notes: This table reports the estimates for the zero-beta excess return and the price of risk for each factor in the Fama and French (1993) three-factor model (FF3) and the Fama and French (2015b) five-factor model (FF5) along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. The factors include the value-weight excess return on the market portfolio (MKT), the size factor (SMB, small minus big), the value factor (HML, high minus low book-to-market), the operating profitability factor (RMW, robust minus weak profitability) and the investment factor (CMA, conservative minus aggressive investment). In addition, I report the sample R^2 for each cross-sectional regression along with its standard error and the p-value for the Kan et al. (2013) specification test of $H_0 : R^2 = 1$. Finally, I report the Kan et al. (2013) misspecification-robust test statistics in square brackets.

Table 7: Equity risk premium predictability

Panel A: scale-wise predictive regressions

		Persistence level						
	$j =$	1	2	3	4	5	6	7
u_t (1)	β_j	17.0671	4.9732	-1.3015	1.2821	-1.4753	**3.0551**	0.3395
	NW t-stat	(1.2109)	(0.6536)	(-0.1805)	(0.3057)	(-0.5219)	(3.8358)	(0.1636)
	HH t-stat	(1.3849)	(0.6896)	(-0.1735)	(0.3544)	(-0.5445)	(3.4481)	(0.2996)
	Adj.R^2 (%)	[0.19%]	[0.08%]	[0.03%]	[0.10%]	[0.40%]	**[4.25%]**	[0.12%]
u_t (3)	β_j	14.4789	8.0920	-1.2110	1.5114	-1.4172	**2.8094**	0.4748
	NW t-stat	(0.9460)	(1.0158)	(-0.1697)	(0.3622)	(-0.5530)	(3.8691)	(0.2462)
	HH t-stat	(1.1196)	(1.0802)	(-0.1647)	(0.4063)	(-0.5929)	(3.2111)	(0.4812)
	Adj.R^2 (%)	[0.13%]	[0.21%]	[0.03%]	[0.16%]	[0.43%]	**[4.42%]**	[0.28%]
u_t (12)	β_j	12.8635	21.4342	-0.5482	3.2158	-1.2089	**4.2765**	1.2757
	NW t-stat	(0.3885)	(1.3916)	(-0.0440)	(0.4033)	(-0.2845)	(3.7904)	(0.4530)
	HH t-stat	(0.4795)	(1.7927)	(-0.0458)	(0.4490)	(-0.3339)	(3.0029)	(1.0020)
	Adj.R^2 (%)	[0.02%]	[0.34%]	[0.00%]	[0.23%]	[0.12%]	**[4.56%]**	[1.00%]
# observations		632	628	620	604	572	508	380

Panel B: long-horizon predictive regressions (forward/backward aggregates)

		Horizon						
	$q =$	16	32	48	64	96	128	192
u_t (1)	β_q	-0.0515	1.1232	2.3776	**2.8096**	**3.8981**	**5.1908**	**2.7207**
	NW t-stat	(-0.0313)	(0.6605)	(1.3904)	(2.4831)	(4.4502)	(10.1284)	(4.4648)
	$t/\sqrt{T}$	{-0.0040}	{0.1158}	{0.2717}	{0.3597}	{0.6867*}	{1.4034***}	{0.4223}
	Adj.R^2 (%)	[-0.16%]	[1.15%]	[6.73%]	**[11.32%]**	**[31.99%]**	**[66.35%]**	**[14.90%]**
u_t (3)	β_q	-0.1223	0.9830	2.2031	**2.6418**	**3.7424**	**4.8934**	**2.1587**
	NW t-stat	(-0.0810)	(0.6294)	(1.3859)	(2.4979)	(4.4820)	(10.1448)	(4.2962)
	$t/\sqrt{T}$	{-0.0103}	{0.1100}	{0.2739}	{0.3666}	{0.7174*}	{1.4596***}	{0.3664}
	Adj.R^2 (%)	[-0.16%]	[1.03%]	[6.83%]	**[11.71%]**	**[33.93%]**	**[68.09%]**	**[11.57%]**
u_t (12)	β_q	-0.0663	2.1299	**4.0386**	**4.6292**	**6.0664**	**7.0527**	0.4706
	NW t-stat	(-0.0325)	(1.2430)	(2.8174)	(5.2286)	(6.0294)	(7.9741)	(1.0098)
	$t/\sqrt{T}$	{-0.0037}	{0.1672}	{0.3734}	{0.4871}	{0.9069**}	{1.5274***}	{0.0651}
	Adj.R^2 (%)	[-0.16%]	[2.56%]	**[12.11%]**	**[19.08%]**	**[45.12%]**	**[70.03%]**	[0.03%]

Notes: Panel A reports the results of scale-wise predictive regressions of the components of S&P 500 index excess returns on the components of macroeconomic uncertainty. For each regression, the table reports OLS estimates of the regressors, Newey-West (1987) and Hansen-Hodrick (1980) corrected t-statistics with $2^j - 1$ lags in parentheses and adjusted R^2 statistics in square brackets. Panel B presents the results of regressions (with an intercept) of forward/backward aggregates over a horizon q. Panel B reports OLS estimates of the regressors, Newey-West (1987) corrected t-statistics with $2 \times (q-1)$ lags in parentheses, Valkanov's (2003) rescaled test statistics in curly brackets and adjusted R^2 statistics in square brackets. Significance at the 5%, 2.5% and 1% level based on the rescaled t-statistic is indicated by *, ** and *** respectively.

Table 8a: Monotonicity tests for horizon-specific risk exposures

Panel A		Size										Top−bottom	MR
		Low	2	3	4	5	6	7	8	9	High	p-value	p-value
Average Return		0.7570	0.7037	0.7728	0.7034	0.7372	0.6721	0.6812	0.6312	0.5724	0.4286	0.0670	0.3972
For returns - $H_0 : R_{10} \geq \ldots \geq R_1$ vs $H_1 : R_{10} < \ldots < R_1$							For risk-loadings - $H_0 : \beta_{10}^{(j)} \leq \ldots \leq \beta_1^{(j)}$ vs $H_1 : \beta_{10}^{(j)} > \ldots > \beta_1^{(j)}$							
$\beta^{(6)}$	$h = 1$	-1.0051	-0.9265	-0.8087	-0.7419	-0.7083	-0.7327	-0.7294	-0.6944	-0.5487	-0.3512	0.0606	0.0656
$\beta^{(6)}$	$h = 3$	-0.9136	-0.8385	-0.7296	-0.6654	-0.6301	-0.6572	-0.6498	-0.6194	-0.4770	-0.2764	0.0606	0.0906
$\beta^{(6)}$	$h = 12$	-1.2469	-1.1572	-0.9866	-0.8730	-0.8108	-0.8857	-0.8641	-0.8236	-0.5952	-0.2726	0.1010	0.2222
$\beta^{(6:7)}$	$h = 1$	-0.8207	-0.8314	-0.7332	-0.7339	-0.7175	-0.7697	-0.7221	-0.7677	-0.5903	-0.4568	0.2696	0.1416
$\beta^{(6:7)}$	$h = 3$	-0.7515	-0.7470	-0.6640	-0.6574	-0.6409	-0.6934	-0.6434	-0.6877	-0.5144	-0.3625	0.2530	0.1580
$\beta^{(6:7)}$	$h = 12$	-0.9683	-0.9940	-0.8915	-0.8734	-0.8424	-0.9727	-0.8778	-0.9557	-0.6915	-0.4531	0.3238	0.3178

Panel B		Long-term Reversal										Top−bottom	MR
		Low	2	3	4	5	6	7	8	9	High	p-value	p-value
Average Return		0.9069	0.7314	0.7297	0.6410	0.6397	0.6077	0.5806	0.5335	0.4058	0.4229	0.0139	0.0036
For returns - $H_0 : R_{10} \geq \ldots \geq R_1$ vs $H_1 : R_{10} < \ldots < R_1$							For risk-loadings - $H_0 : \beta_{10}^{(j)} \leq \ldots \leq \beta_1^{(j)}$ vs $H_1 : \beta_{10}^{(j)} > \ldots > \beta_1^{(j)}$							
$\beta^{(6)}$	$h = 1$	-1.3095	-0.7870	-0.9055	-0.7816	-0.6135	-0.4687	-0.4758	-0.3173	-0.1509	-0.0635	0.0014	0.4644
$\beta^{(6)}$	$h = 3$	-1.2286	-0.7282	-0.8301	-0.7010	-0.5419	-0.4071	-0.4061	-0.2596	-0.0881	0.0081	0.0012	0.4094
$\beta^{(6)}$	$h = 12$	-1.8966	-1.0688	-1.2519	-0.9897	-0.7372	-0.5128	-0.4981	-0.2578	0.0839	0.3111	0.0018	0.4962
$\beta^{(6:7)}$	$h = 1$	-1.1734	-0.7088	-0.9100	-0.8408	-0.6730	-0.4944	-0.4755	-0.3618	-0.1889	-0.2685	0.0204	0.6342
$\beta^{(6:7)}$	$h = 3$	-1.0994	-0.6460	-0.8264	-0.7513	-0.5930	-0.4237	-0.4041	-0.2936	-0.1155	-0.1703	0.0122	0.6016
$\beta^{(6:7)}$	$h = 12$	-1.6565	-0.9083	-1.2608	-1.1076	-0.8581	-0.5513	-0.5439	-0.3511	-0.0044	-0.0178	0.0100	0.6952

Panel C		Short-term Reversal										Top−bottom	MR
		Low	2	3	4	5	6	7	8	9	High	p-value	p-value
Average Return		0.5719	0.7780	0.7194	0.6226	0.5764	0.4955	0.4574	0.4830	0.3015	0.1794	0.0182	0.6822
For returns - $H_0 : R_{10} \geq \ldots \geq R_1$ vs $H_1 : R_{10} < \ldots < R_1$							For risk-loadings - $H_0 : \beta_{10}^{(j)} \leq \ldots \leq \beta_1^{(j)}$ vs $H_1 : \beta_{10}^{(j)} > \ldots > \beta_1^{(j)}$							
$\beta^{(6)}$	$h = 1$	-0.9308	-0.6956	-0.6245	-0.3368	-0.5560	-0.4400	-0.4034	-0.4340	-0.2983	-0.2014	0.0128	0.8368
$\beta^{(6)}$	$h = 3$	-0.8324	-0.6163	-0.5412	-0.2696	-0.4806	-0.3637	-0.3362	-0.3589	-0.2299	-0.1371	0.0140	0.8566
$\beta^{(6)}$	$h = 12$	-1.0707	-0.8151	-0.6815	-0.2608	-0.6172	-0.4075	-0.3842	-0.3818	-0.1900	0.0194	0.0280	0.8844
$\beta^{(6:7)}$	$h = 1$	-0.9351	-0.7028	-0.6727	-0.3597	-0.6193	-0.5546	-0.4947	-0.5464	-0.4792	-0.2949	0.0250	0.8074
$\beta^{(6:7)}$	$h = 3$	-0.8286	-0.6116	-0.5759	-0.2817	-0.5319	-0.4646	-0.4122	-0.4561	-0.3854	-0.2241	0.0274	0.8214
$\beta^{(6:7)}$	$h = 12$	-1.0747	-0.8353	-0.7844	-0.3036	-0.7376	-0.6326	-0.5390	-0.5534	-0.4512	-0.1171	0.0492	0.8318

Notes: This table presents the horizon-specific risk exposures with respect to the factors $\Delta u_t^{(6)}$ and $\Delta u_t^{(6:7)}$ for $h = 1, 3, 12$ for various one-way portfolio sorts and the corresponding monotonicity tests. The sorting variables are: size (Panel A), long-term reversal (Panel B) and short-term reversal (Panel C). The first row in each panel reports average excess returns (in percent per month) for the test assets. The final column in each panel presents the p-value for the monotonic relation (MR) test. The penultimate column presents the bootstrap p-value for the top-minus-bottom difference in the corresponding returns and scale-wise betas.

Table 8b: Monotonicity tests for horizon-specific risk exposures

Panel D		Book-to-Market					Top−bottom	MR
		Low	2	3	4	High	p-value	p-value
Average Return		0.4200	0.5385	0.5701	0.6902	0.8421	0.0033	0.0078
For returns - $H_0 : R_5 \leq \ldots \leq R_1$ vs $H_1 : R_5 > \ldots > R_1$								
For risk-loadings - $H_0 : \beta_5^{(j)} \geq \ldots \geq \beta_1^{(j)}$ vs $H_1 : \beta_5^{(j)} < \ldots < \beta_1^{(j)}$								
$\beta^{(6)}$	$h = 1$	-0.3088	-0.5302	-0.7102	-0.8052	-0.7867	0.0112	0.0462
$\beta^{(6)}$	$h = 3$	-0.2374	-0.4622	-0.6278	-0.7258	-0.7093	0.0126	0.0418
$\beta^{(6)}$	$h = 12$	-0.1874	-0.5846	-0.8600	-1.0516	-1.0232	0.0142	0.0344
$\beta^{(6:7)}$	$h = 1$	-0.4482	-0.5226	-0.7029	-0.7677	-0.7427	0.2038	0.0978
$\beta^{(6:7)}$	$h = 3$	-0.3534	-0.4507	-0.6197	-0.6895	-0.6731	0.1716	0.0782
$\beta^{(6:7)}$	$h = 12$	-0.3967	-0.5988	-0.8744	-1.0284	-1.0160	0.1292	0.0404
Panel E		Investment					Top−bottom	MR
		Low	2	3	4	High	p-value	p-value
Average Return		0.7585	0.5776	0.5203	0.5129	0.4030	0.0034	0.0240
For returns - $H_0 : R_5 \geq \ldots \geq R_1$ vs $H_1 : R_5 < \ldots < R_1$								
For risk-loadings - $H_0 : \beta_5^{(j)} \leq \ldots \leq \beta_1^{(j)}$ vs $H_1 : \beta_5^{(j)} > \ldots > \beta_1^{(j)}$								
$\beta^{(6)}$	$h = 1$	-0.7509	-0.5922	-0.5566	-0.4761	-0.1936	0.0050	0.0052
$\beta^{(6)}$	$h = 3$	-0.6774	-0.5274	-0.4775	-0.3953	-0.1201	0.0060	0.0034
$\beta^{(6)}$	$h = 12$	-0.9480	-0.7339	-0.6222	-0.4407	0.0781	0.0076	0.0034
$\beta^{(6:7)}$	$h = 1$	-0.7146	-0.6328	-0.6323	-0.5333	-0.2676	0.0394	0.0330
$\beta^{(6:7)}$	$h = 3$	-0.6385	-0.5644	-0.5431	-0.4425	-0.1809	0.0336	0.0186
$\beta^{(6:7)}$	$h = 12$	-0.8805	-0.8331	-0.7714	-0.5562	-0.0329	0.0294	0.0128
Panel F		Dividend Yield					Top−bottom	MR
		Low	2	3	4	High	p-value	p-value
Average Return		0.4520	0.5479	0.5028	0.6402	0.6058	0.1909	0.3302
For returns - $H_0 : R_5 \leq \ldots \leq R_1$ vs $H_1 : R_5 > \ldots > R_1$								
For risk-loadings - $H_0 : \beta_5^{(j)} \geq \ldots \geq \beta_1^{(j)}$ vs $H_1 : \beta_5^{(j)} < \ldots < \beta_1^{(j)}$								
$\beta^{(6)}$	$h = 1$	0.0139	-0.4367	-0.6084	-0.6519	-1.0399	0.0002	0.0044
$\beta^{(6)}$	$h = 3$	0.0670	-0.3637	-0.5436	-0.5818	-0.9337	0.0004	0.0058
$\beta^{(6)}$	$h = 12$	0.3794	-0.4203	-0.7676	-0.8340	-1.3937	0.0004	0.0048
$\beta^{(6:7)}$	$h = 1$	-0.1342	-0.4913	-0.5693	-0.6434	-1.0320	0.0078	0.0022
$\beta^{(6:7)}$	$h = 3$	-0.0578	-0.4056	-0.5052	-0.5662	-0.9306	0.0064	0.0034
$\beta^{(6:7)}$	$h = 12$	0.1636	-0.5196	-0.7459	-0.8461	-1.4417	0.0022	0.0030

Notes: This table presents the horizon-specific risk exposures with respect to the factors $\Delta u_t^{(6)}$ and $\Delta u_t^{(6:7)}$ for $h = 1, 3, 12$ for various one-way portfolio sorts and the corresponding monotonicity tests. The sorting variables are: book-to-market (Panel D), investment (Panel E) and dividend-yield (Panel F). The first row in each panel reports average excess returns (in percent per month) for the test assets. The final column in each panel presents the p-value for the monotonic relation (MR) test. Similarly, the penultimate column presents the bootstrap p-value for the top-minus-bottom difference in the corresponding returns and scale-wise betas.

Internet Appendix for

"Business-Cycle Variation in Macroeconomic Uncertainty and the Cross-Section of Expected Returns: Evidence for Horizon-Dependent Risks"

Georgios Xyngis

Not Intended for Publication

This appendix contains additional results and robustness checks that are omitted in the main paper for brevity.

Same burn-in period

In the main paper, I discard the first $2^j - 1$ observations for each scale, that is, I use a burn-in specific period for each component and rely on the maximum number of observations possible for each horizon to conduct statistical and economic inferences. Here I adopt a different approach to initialize the filtering procedure. Specifically, I use the same burn-in period for all components which implies a reduction of the effective sample for $j \in \{1, 2, 3, 4, 5, 6\}$. Tables IA.1 through IA.4 present the results from the cross-sectional regressions for the same sub-period. The results for all test assets remain quantitatively similar.

Uncertainty shocks with persistence greater than 128 months

I report the results for low-frequency uncertainty shocks with persistence greater than $2^7 = 128$ months (see Table IA.5). The factor $\Delta u_t^{(>7)}$ cannot explain the cross-sectional variation in the

25 FF size and book-to-market portfolios, the 25 FF size and investment and the 25 FF size and variance portfolios. Also, the null that the model is correctly specified (i.e. $H_0: R^2 = 1$) is strongly rejected. In contrast, low-frequency uncertainty shocks with persistence greater than 128 months are priced in the cross-section of the 25 FF book-to-market and operating profitability portfolios. However, the estimates of the zero-beta excess return are statistically significant at the 1% level for all $h = 1, 3, 12$. Also, the factor has a higher MAPE in comparison with $\Delta u_t^{(6:7)}$ and the specification test rejects the hypothesis of a perfect fit. In addition, the explanatory power of the factor is limited. (i.e. for $h = 1$: $se(\widehat{\mathrm{R}^2_{(>7)}}) = 0.085$, for $h = 3$: $se(\widehat{\mathrm{R}^2_{(>7)}}) = 0.084$ and for $h = 12$: $se(\widehat{\mathrm{R}^2_{(>7)}}) = 0.081$). Similar results (see Table IA.6) hold for low-frequency uncertainty shocks with persistence ranging between 128 and 256 months (i.e. the priced factor is $\Delta u_t^{(8)}$). Also, confidence intervals for the sample cross-sectional R^2 for $\Delta u_t^{(>7)}$ and $\Delta u_t^{(8)}$ are available in Table IA.7.

Results for the low-frequency macro volatility risk factor of Boons and Tamoni (2015) - monthly data

In line with Boons and Tamoni (2015) I extract from the volatility of monthly industrial production low-frequency shocks with persistence greater than 32 months. Note that IPVOL is estimated using an $\mathrm{AR}(1) - \mathrm{GARCH}(1,1)$ model over the full sample. Table IA.8 reports the estimates for the zero-beta excess return and the price of risk for the innovations in macro volatility shocks with persistence greater than 32 months. The factor $\Delta IPVOL_t^{(>5)}$ is not priced in any of the test assets. From this perspective my study complements Boons and Tamoni (2015) by showing that investors care about horizon-dependent economic uncertainty irrespective of their portfolio rebalancing period.

5 industry portfolios *plus* 25 FF size and book-to-market

Following the suggestion of Lewellen et al. (2010) and Daniel and Titman (2012) I relax the tight (i.e. low-dimensional) factor structure of the test assets and I use the 25 FF size and book-to-market and the 5 FF industry portfolios which are priced together. That is, I include the industry portfolios to provide a higher hurdle for the proposed factor (i.e. the cross-sectional variation in the expected returns is higher). Since the asymptotic results in Kan et al. (2013) become less reliable as the number of test assets increases (e.g. the asymptotic distribution of the sample cross-sectional R^2), I only add the 5 industry portfolios. The results in Table IA.9 remain similar and the model with the *business-cycle uncertainty* factor is correctly specified.

Controlling for Fama-French factors

Table IA.10 presents results from cross-sectional regressions where I control for exposure to the Fama-French's factors. The control factors include the value-weight excess return on the market portfolio (MKT), the size factor (SMB, small minus big), the value factor (HML, high minus low book-to-market), the operating profitability factor (RMW, robust minus weak profitability) and the investment factor (CMA, conservative minus aggressive investment). Except for the test assets sorted across book-to-market and operating profitability, the *business-cycle uncertainty* factor remains statistically significant in the presence of the control factors (see also the discussion in Section 3.3. of the main paper).

Controlling for momentum, short-term reversal, long-term reversal, liquidity and portfolio characteristics

Tables IA.11a and IA.11b report estimates for the price of risk ($\lambda_{6:7}$) for $u_t^{(6:7)}$ after controlling for exposure to the value-weight excess return on the market portfolio (MKT), the size factor (SMB), the value factor (HML), the momentum factor (MOM), the short-term reversal factor (STR), the long-term reversal factor (LTR), the liquidity factor (LIQ), the log size ($\log(ME)$) and the log book-to-market ratio ($\log(B/M)$). I estimate the risk exposures for the MKT, SMB, HML, MOM, STR and LTR factors using the same time-series regression and the risk-loadings for the LIQ factor separately as in Pastor and Stambaugh (2003). The *business-cycle uncertainty* factor remains statistically significant in the presence of the control factors.

Residuals from an AR(1) model fitted to $u_t^{(6:7)}$

Under the one-sided, linear Haar filter used for the extraction decomposing across horizons changes in aggregate uncertainty is equivalent to calculating changes in the horizon-specific uncertainty series. Thus, in the main paper I estimate the innovations in the horizon-specific uncertainty components by first-differencing each series. For robustness, I present in Table IA.12 the cross-sectional estimates for the *business-cycle uncertainty* factor where the innovations are the residuals from an AR(1) model fitted to the factor $u_t^{(6:7)}$. The results remain quantitatively similar across all test assets.

Bootstrapped confidence intervals for the first and second-pass cross-sectional estimates

I calculate confidence intervals for the first-pass horizon-dependent betas for $u_t^{(6:7)}$ using the bias-corrected percentile method and the stationary bootstrap procedure described in Appendix A. For a survey of bootstrap procedures for constructing confidence regions see Diciccio and Romano (1988). The results are available in Table IA.13. Bold values denote statistically significant beta estimates at a 90% confidence level. Several of the estimated betas are individually statistical significant, that is, the bootstrap-based confidence regions do not include zero.

Moreover, for each bootstrap replication $b = 1, \ldots, 5,000$ I estimate a cross-sectional regression of average portfolio excess returns (original data) on the pseudo-sample of the horizon-specific risk exposures. I report confidence intervals using the bias-corrected percentile method for the zero-beta excess return ($\lambda_{0,6:7}$), the price of risk ($\lambda_{6:7}$) and the sample R^2. The results are available in Table IA.14. The main difference with the results in the main paper is that for the 25 FF book-to-market and operating profitability portfolios the estimates of the zero-beta excess return remain statistically significant. Two comments are in order here. First, for these test assets the model is misspecified. Second, the horizon-specific risk exposures are estimated with error in the first-pass scale-wise regression. In contrast, the popular Fama-MacBeth (1973) test-statistics reported in the main paper do not account for estimation errors in the betas or for a potentially misspecified model. Note that since the first-pass regressions are scale-wise, the Shanken (1992) correction or the misspecification-robust t-statistics of Kan et al. (2013) are not directly applicable here.

Bootstrapped confidence intervals for the scale-wise predictive regressions

Table IA.15 reports bootstrapped confidence intervals for the scale-wise predictive regressions for $j = 6, 7$ using the bias-corrected percentile method and the stationary bootstrap of Politis and Romano (1994). In Panel A of Table IA.15 the average block size in this case is set equal to 32 - calculated based on the Politis and White (2004) estimator. In Panel B of Table IA.15 the block size is set equal to 2^j. For $j = 6$ the coefficients from the scale-wise predictive regressions are statistically significant.

Valkanov's (2003) rescaled t-statistic

The standard t-statistics in long-horizon regressions do not converge to well-defined distributions (for instance, see Valkanov, 2003 and Bandi and Perron, 2008). To address this inferential problem I rely on Valkanov's (2003) rescaled $t/\sqrt{T}$ statistic. In particular, as in Valkanov's framework I assume that the underlying data-generating processes are

$$r^e_{t+1} = \beta u_t + \epsilon_{1,t+1} \tag{IA.1}$$

$$u_t = \varrho u_{t-1} + \epsilon_{2,t+1} \tag{IA.2}$$

where $\rho = 1 + c/T$ and the parameter c measures deviations from unity in a decreasing (at rate T) neighbourhood of 1. Also, I assume that the vector $[\epsilon_{1,t+1}\,, \epsilon_{2,t+1}\,]$ is a vector martingale difference sequence with covariance matrix $\left[\sigma^2_{11}\,\sigma_{12}; \sigma_{21}\,\sigma^2_{22}\right]$. Following Bandi and Perron (2008) I let the portion of the overlap to be a constant fraction of the sample size, that is, $h = [\lambda T]$. Table IA.16 reports the right-tail critical values of $t/\sqrt{T}$ at various percentiles. I simulate the distribution of $t/\sqrt{T}$ for samples of length $T = 635$. I implement 5,000 replications. It is important to highlight that I only adopt this framework to address the inferential problems that arise in predictive regressions with persistent regressors. As I demonstrate in Table IA.17 the data-generating process for uncertainty is a multi-scale autoregressive process, i.e. a system in which high-frequency shocks are not linear combinations of low-frequency shocks (see also the novel work of Bandi et al., 2015).

Multi-scale autoregressive system

Table IA.17 reports the estimation results of the multi-scale autoregressive system for macro uncertainty. For $j \in \{1, 5\}$ the uncertainty components can be represented as scale-wise AR processes, i.e. $u^{(j)}_{k\times 2^j+2^j} = \rho_j u^{(j)}_{k\times 2^j} + \varepsilon^{(j)}_{k\times 2^j+2^j}$ where $k \in Z$. My results are similar with the estimates for consumption shocks in Ortu et al. (2013) (see page 2905). Note that as Bandi et al. (2015) point out the dependence ρ_j in time-scale j is significantly lower than the dependence of the raw series. Moreover, I estimate the half-life for each autoregressive component which is given by:

$$HL\left(j\right) = \frac{\ln\left(0.5\right)}{\ln\left(|\rho_j|\right)} \times 2^j. \tag{IA.3}$$

The presence of the factor 2^j is justified on the basis that the decimated component at time-scale j is defined on the grid $\left\{k \times 2^j : \, k\in \mathbb{Z}\right\}$. The estimated half-life for $j = 1$ is close to the lower bound of the corresponding interval $[2^{j-1}, 2^j)$ while for $j = 5$ lies in the middle.

In line with the novel work of Bandi et al. (2015), these results imply a Wold-type representation for the macroeconomic uncertainty series of the following kind:

$$u_t = \sum_{j=1}^{J}\sum_{k=0}^{\infty} \alpha_{j,k}\varepsilon^{(j)}_{t-k\times 2^j} + \sum_{k=0}^{\infty} b_{J,k}\pi^{(J)}_{\varepsilon,t-k\times 2^J,t-(k+1)\times 2^J+1} \tag{IA.4}$$

where $\varepsilon_t^{(j)} = u_t^{(j)} - \mathcal{P}_{\mathcal{M}_{j,t-2^j}} u_t^{(j)}$ and $\mathcal{P}_{\mathcal{M}_{j,t-2^j}}$ is a projection mapping[23] into the closed subspace $\mathcal{M}_{j,t-2^j}$ spanned by $\left\{u_{t-k\times 2^j}^{(j)}\right\}_{k\in\mathbb{Z}}$, $\alpha_{j,k} = E\left(u_t, \varepsilon_{t-k\times 2^j}^{(j)}\right)$, $b_{J,k} = E\left(u_t, \pi_{\varepsilon,t-k\times 2^J,t-(k+1)\times 2^J+1}^{(J)}\right)$ and $\pi_{\varepsilon,t-k\times 2^J,t-(k+1)\times 2^J+1}^{(J)} = \sqrt{2^J}\left(\frac{\sum_{i=t-(k+1)\times 2^J+1}^{t-k\times 2^J}\varepsilon_i}{2^J}\right)$ with $\varepsilon_t = u_t - \mathcal{P}_{\mathcal{M}_{t-1}} u_t$ satisfying $\mathrm{Var}\left(\varepsilon_t\right) = 1$. The real coefficients $\alpha_{j,k}$ are obtained by projecting u_t on the linear subspace of $L^2\left(\Omega, \mathcal{F}, \mathcal{P}\right)$ generated by $\varepsilon_{t-k\times 2^j}^{(j)}$ and can be viewed as scale-specific impulse response functions that capture the effect of shocks localized at a specific level of resolution. This modelling approach of Bandi et al. (2015) generates a separation between scales in terms of their information content (e.g. shocks are scale-specific). Note that if $\varepsilon_t^{(j)} = \sqrt{2^j}\left(\frac{\sum_{i=0}^{2^{j-1}-1}\varepsilon_{t-i}}{2^{j-1}} - \frac{\sum_{i=0}^{2^j-1}\varepsilon_{t-i}}{2^j}\right)$, i.e. if the information contained at every scale is an aggregate of that contained at higher frequencies Equation (IA.4) will reduce to a classical Wold decomposition (a proof is available in Bandi et al., 2015).

Percentage contribution of $u_t^{(j)}$ and $IPVOL_t^{(j)}$ to total variance

Panel A of Table IA.18 shows the percentage contribution of each individual component to the total variance of the time-series for aggregate uncertainty. Approximate confidence intervals for the variance of the components are computed based on the Chi-squared distribution with one degree of freedom (see also Percival, 1995). Note that by definition $\mathrm{Var}\left(u_t\right) = \sum_{j=1}^{J}\mathrm{Var}\left(u_t^{(j)}\right) + \mathrm{Var}\left(u_t^{(>J)}\right)$. The first seven persistent components filtered out of the uncertainty index account for 74.91% of the total variance of the series. Fluctuations in uncertainty with persistence ranging between 1 and 2 months (i.e. high-frequency) account only for 0.65% of the total variance with a lower and an upper confidence bounds of 0.56% and 0.77% respectively. Low-frequency fluctuations with persistence between 32 and 64 months explain 22.89% of the total variance with a lower and an upper confidence

[23] For an introduction to Hilbert spaces and techniques see Brockwell and Davis (2009), Chapter 2.

bounds of 14.51% and 41.42% respectively. Similarly, shocks with persistence between 64 and 128 months explain 18.73% of the total variation in the series with a lower and an upper confidence bounds of 9.55% and 52.02% respectively. Figure IA.1 depicts the horizon-specific contribution of each component to the variance of the uncertainty series along with a comparison of the different methods for constructing confidence intervals.

Panel B of Table IA.18 presents the percentage contribution of each individual component to the total variance for the volatility of industrial production. Shocks with persistence greater than 32 months (i.e. $IPVOL_t^{(>5)}$) account only for 12.07% of the total variance of the series.

Beta comparison: $\boldsymbol{\beta}^{(6:7)}$ versus $\boldsymbol{\beta}^{(6)}\boldsymbol{\varpi}^{(6)} + \boldsymbol{\beta}^{(7)}\boldsymbol{\varpi}^{(7)}$

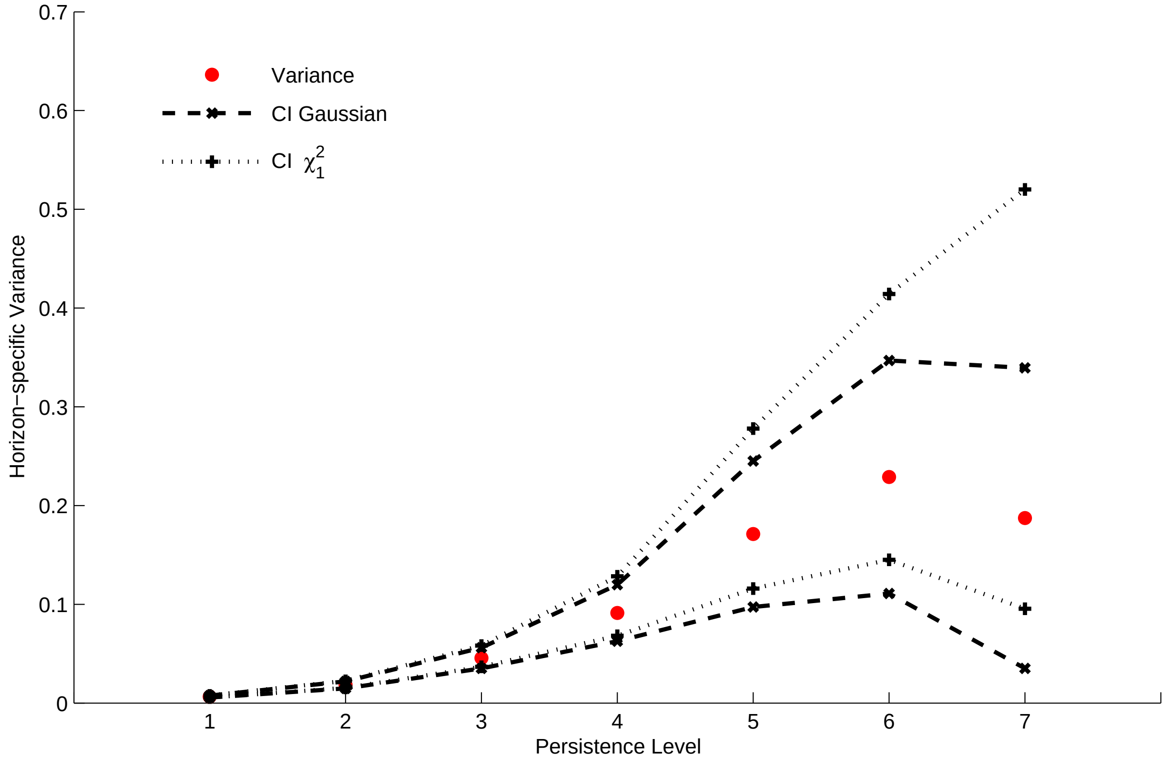
In Equation (11) $\beta^{(6:7)}$ can be viewed as a linear combination of $\beta^{(6)}$ and $\beta^{(7)}$ with weights depending on the relative contribution of the corresponding factor to total variance. The extracted components are only *nearly-uncorrelated* across scales (i.e. $Cov\left(\Delta u_t^{(6)}, \Delta u_t^{(7)}\right) \simeq 0$) and therefore this relation is not exact. In Figure IA.2 I illustrate the difference by plotting $\beta^{(6:7)}$ versus $\beta^{(6)}\varpi^{(6)} + \beta^{(7)}\varpi^{(7)}$ for the size and book-to-market portfolios. I estimate $\beta^{(6)}$ and $\beta^{(7)}$ over the same sub-period where $\varpi^{(6)} = 0.8647$ and $\varpi^{(7)} = 1 - \varpi^{(6)}$. Note that Bandi and Tamoni (2015) follow a similar approach to calculate a business-cycle consumption factor, however, they use the decimated components which are uncorrelated across scales.

Tests of Equality of Cross-Sectional R^2's

Finally, I compare the two competing beta pricing models based on the factors $\Delta u_t^{(6)}$ and $\Delta u_t^{(6:7)}$ by asking whether they have the same population cross-sectional R^2. My analysis is similar in spirit with Kan et al. (2013). However, the sequential testing procedure suggested by Vuong (1989) and described in Kan et al. (2013) is not applicable here since the two models are non-nested and *distinct*[24]. Therefore, I perform directly the normal test of $H_0 : 0 < \mathrm{R}^2_{(6)} = \mathrm{R}^2_{(6:7)} < 1$, that is, I assume that both models are not perfectly specified (i.e. I check if the population R^2's are equal for some value less than one) and rule out the scenario that the two beta pricing models are completely irrelevant for explaining expected returns. Table IA.19 reports the results of the tests of equality of the cross-sectional R^2's where both models are estimated over the same period. There are no sufficient evidence across all test assets to reject the null hypothesis. Two observations emerge from the results in Table IA.19. First, the limited precision of the estimates makes it difficult to conclude whether one model consistently outperforms the other. That is, even cases of large R^2 differences do not give rise to statistical rejections due to the high sampling variability of the cross-sectional R^2's. Kan and Robotti (2009) and Kan et al. (2013) report similar problems in the comparison of linear asset pricing models using aggregate measures of pricing errors. Second, it is hard to distinguish between the two models since the relative contribution of $\Delta u_t^{(7)}$ in Equation (11) is small (i.e. $\varpi^{(6)} > \varpi^{(7)}$).

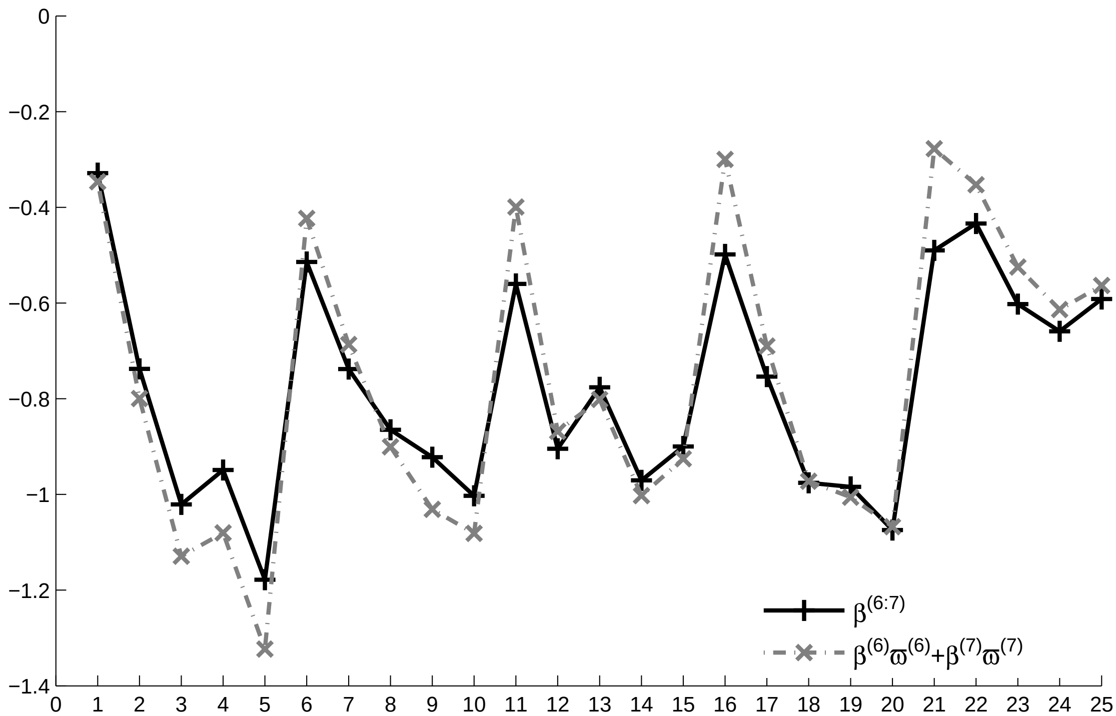
[24] For instance, consider two competing beta pricing models. Let f_{1t}, f_{2t} and f_{3t} be three sets of distinct factors at time t where f_{it} is of dimension $K_i \times 1$, $i = 1, 2, 3$. Assume that model 1 uses f_{1t} and f_{2t} as factors while model 2 uses f_{1t} and f_{3t}. When $K_2 = 0$ model 2 nests 1 as a special case. Similarly, when $K_3 = 0$ model 1 nests model 2. When $K_2 > 0$ and $K_3 > 0$ the two models are non-nested. Finally, when $K_2, K_3 > 0$ and $K_1 = 0$ the two models are non-nested and distinct.

Figure IA.1: Horizon-specific contribution to variance



Notes: This figure plots the horizon-specific contributions to the time series of aggregate uncertainty (derived from monthly forecasts) along with the relevant confidence bounds.

Figure IA.2: Beta comparison: $\beta^{(6:7)}$ versus $\beta^{(6)}\varpi^{(6)} + \beta^{(7)}\varpi^{(7)}$



Notes: This figure plots $\beta^{(6:7)}$ versus $\beta^{(6)}\varpi^{(6)} + \beta^{(7)}\varpi^{(7)}$ for the size and book-to-market portfolios. I estimate $\beta^{(6)}$ and $\beta^{(7)}$ over the same sub-period (i.e. I discard the first $2^7 - 1$ observations) where $\varpi^{(6)} = 0.8647$ and $\varpi^{(7)} = 1 - \varpi^{(6)}$.

Table IA.1: Cross-sectional regression with the same burn-in period: 25 FF size and book-to-market portfolios

	Persistence level							
$j =$	1	2	3	4	5	6	7	6:7
$u_t(1)$								
$\lambda_{0,j}$	0.8872	0.9814	1.0401	0.5502	0.3493	0.2078	0.5814	0.0581
	(2.8483)	(3.3550)	(4.1622)	(2.4048)	(1.4251)	(0.8401)	(2.3717)	(0.2083)
λ_j	0.3719	0.4399	0.5986	-0.1891	-0.3654	-0.5922	-0.4016	-0.8315
	(0.5038)	(0.8220)	(1.2698)	(-0.6207)	(-1.3914)	(-3.9006)	(-3.2124)	(-4.3264)
price of risk	0.401%	0.623%	0.939%	-0.286%	-0.844%	-2.090%	-2.295%	-2.274%
R^2	2.303%	5.547%	12.586%	1.172%	10.168%	62.416%	75.271%	73.891%
$se(\widehat{\mathrm{R}^2})$	0.0846	0.1266	0.1681	0.0431	0.1603	0.2183	0.2375	0.1224
$p\left(\mathrm{R}^2 = 1\right)$	0.0157	0.0186	0.0225	0.0175	0.0212	0.1692	0.2956	0.3139
MAPE	2.029%	2.077%	2.025%	1.949%	1.752%	1.091%	1.156%	1.114%
$u_t(3)$								
$\lambda_{0,j}$	0.8213	0.9419	1.0123	0.5725	0.3148	0.2364	0.5836	0.1109
	(2.9482)	(3.1862)	(3.8181)	(2.1542)	(1.2817)	(0.9652)	(2.4041)	(0.4097)
λ_j	0.1154	0.2264	0.4008	-0.1399	-0.4083	-0.6232	-0.4259	-0.8476
	(0.3574)	(0.6799)	(1.0331)	(-0.4201)	(-1.5297)	(-3.9064)	(-3.3841)	(-4.3044)
price of risk	0.287%	0.532%	0.801%	-0.233%	-0.950%	-2.107%	-2.340%	-2.285%
R^2	1.175%	4.037%	9.167%	0.776%	12.888%	63.443%	78.251%	74.617%
$se(\widehat{\mathrm{R}^2})$	0.0656	0.1123	0.1586	0.0402	0.1832	0.2211	0.2066	0.1311
$p\left(\mathrm{R}^2 = 1\right)$	0.0164	0.0179	0.0220	0.0167	0.0226	0.1765	0.3255	0.3229
MAPE	2.059%	2.063%	2.052%	1.965%	1.717%	1.079%	1.075%	1.079%
$u_t(12)$								
$\lambda_{0,j}$	0.7899	0.9717	1.0263	0.4595	0.2511	0.3083	0.6407	0.2278
	(3.2865)	(3.5045)	(3.8459)	(1.6573)	(1.0452)	(1.2606)	(2.6882)	(0.8350)
λ_j	0.0597	0.1283	0.1854	-0.1238	-0.2727	-0.3784	-0.2284	-0.4856
	(0.3289)	(0.8453)	(1.0747)	(-0.7572)	(-1.9470)	(-3.9801)	(-2.9019)	(-4.0302)
price of risk	0.221%	0.679%	0.835%	-0.457%	-1.223%	-2.174%	-2.182%	-2.336%
R^2	0.696%	6.587%	9.958%	2.986%	21.366%	67.543%	68.037%	77.922%
$se(\widehat{\mathrm{R}^2})$	0.0425	0.1435	0.1654	0.0850	0.2285	0.2049	0.2665	0.1147
$p\left(\mathrm{R}^2 = 1\right)$	0.0045	0.0196	0.0224	0.0168	0.0296	0.2109	0.1920	0.3653
MAPE	2.057%	2.058%	2.031%	1.880%	1.602%	1.039%	1.315%	1.029%
# observ.	507							

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,j}$) and the price of risk (λ_j) for each scale j along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I normalize the scale-wise risk exposures and estimate the price of risk per unit of cross-sectional standard deviation in exposure in percent per year. I also report the sample R^2 for each cross-sectional regression and its standard error, the p-value for the Kan et al. (2013) test of $H_0: R^2 = 1$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year.

Table IA.2: Cross-sectional regression with the same burn-in period: 25 FF size and investment portfolios

	Persistence level							
$j =$	1	2	3	4	5	6	7	6:7
$u_t\,(1)$								
$\lambda_{0,j}$	0.9391	0.9872	1.1510	0.6117	0.2569	0.3080	0.7261	0.1923
	(4.5809)	(4.9284)	(6.3034)	(2.2124)	(0.9453)	(1.2341)	(2.9121)	(0.6872)
λ_j	0.2204	0.2402	0.6047	-0.2596	-0.6163	-0.6327	-0.4063	-0.8591
	(0.5611)	(0.7201)	(1.8107)	(-0.5637)	(-1.9119)	(-3.5367)	(-3.8261)	(-4.6799)
price of risk	0.353%	0.471%	1.037%	-0.344%	-1.227%	-2.139%	-1.927%	-2.212%
R^2	1.862%	3.312%	16.054%	1.763%	22.461%	68.268%	55.409%	73.006%
$se(\widehat{\mathrm{R}^2})$	0.0714	0.0903	0.1607	0.0627	0.2058	0.1968	0.2299	0.0922
$p\left(\mathrm{R}^2 = 1\right)$	0.0123	0.0108	0.0256	0.0079	0.0094	0.1465	0.0833	0.2508
MAPE	2.132%	2.108%	1.927%	2.088%	1.760%	0.835%	1.364%	0.985%
$u_t\,(3)$								
$\lambda_{0,j}$	0.7808	0.9588	1.0764	0.5910	0.2313	0.3454	0.7391	0.2531
	(3.0598)	(4.2776)	(5.7037)	(1.9993)	(0.8556)	(1.4005)	(3.0064)	(0.9309)
λ_j	-0.0250	0.1290	0.3366	-0.2447	-0.6571	-0.6545	-0.4400	-0.8672
	(-0.0857)	(0.5183)	(1.1657)	(-0.5785)	(-2.0648)	(-3.5701)	(-4.1403)	(-4.6254)
price of risk	-0.066%	0.357%	0.726%	-0.383%	-1.360%	-2.153%	-2.028%	-2.227%
R^2	0.066%	1.902%	7.868%	2.190%	27.604%	69.186%	61.365%	74.027%
$se(\widehat{\mathrm{R}^2})$	0.0146	0.0720	0.1294	0.0746	0.2236	0.1942	0.2099	0.0934
$p\left(\mathrm{R}^2 = 1\right)$	0.0114	0.0107	0.0220	0.0081	0.0104	0.1566	0.1119	0.2645
MAPE	2.151%	2.132%	2.061%	2.077%	1.668%	0.817%	1.256%	0.963%
$u_t\,(12)$								
$\lambda_{0,j}$	0.9459	0.9549	1.0526	0.3977	0.2035	0.4250	0.8018	0.4021
	(4.5562)	(4.4838)	(5.5522)	(1.3158)	(0.7773)	(1.7359)	(3.3523)	(1.4791)
λ_j	0.0810	0.0587	0.1352	-0.2208	-0.3997	-0.3929	-0.2238	-0.4750
	(0.5789)	(0.5494)	(1.0451)	(-1.1216)	(-2.5562)	(-3.7941)	(-3.2885)	(-4.5760)
price of risk	0.390%	0.391%	0.647%	-0.782%	-1.679%	-2.205%	-1.771%	-2.166%
R^2	2.270%	2.283%	6.248%	9.129%	42.082%	72.563%	46.790%	70.012%
$se(\widehat{\mathrm{R}^2})$	0.0844	0.0825	0.1144	0.1505	0.2409	0.1742	0.2467	0.1424
$p\left(\mathrm{R}^2 = 1\right)$	0.0116	0.0162	0.0225	0.0053	0.0176	0.2061	0.0715	0.2089
MAPE	2.126%	2.131%	2.088%	1.925%	1.401%	0.792%	1.459%	1.078%
# observ.	472							

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,j}$) and the price of risk (λ_j) for each scale j along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I normalize the scale-wise risk exposures and estimate the price of risk per unit of cross-sectional standard deviation in exposure in percent per year. I also report the sample R^2 for each cross-sectional regression and its standard error, the p-value for the Kan et al. (2013) test of $H_0:\ R^2 = 1$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year.

Table IA.3: Cross-sectional regression with the same burn-in period: 25 FF book-to-market and operating profitability portfolios

	Persistence level							
$j =$	1	2	3	4	5	6	7	6:7
$u_t(1)$								
$\lambda_{0,j}$	0.8186	1.2477	0.8519	0.1140	0.2877	0.3041	0.6235	0.2989
	(3.3733)	(4.2837)	(3.9400)	(0.4268)	(1.2030)	(1.2003)	(2.7259)	(1.1748)
λ_j	0.2089	0.8050	0.2607	-0.7548	-0.5021	-0.5992	-0.4767	-0.6375
	(0.5940)	(1.8648)	(0.7979)	(-2.8855)	(-2.4681)	(-3.4823)	(-3.3816)	(-3.3535)
price of risk	0.267%	1.193%	0.486%	-1.584%	-1.426%	-2.638%	-2.806%	-2.322%
R^2	0.521%	10.370%	1.718%	18.290%	14.831%	50.719%	57.417%	39.300%
$se(\widehat{R^2})$	0.0177	0.0924	0.0431	0.0607	0.1043	0.1454	0.1781	0.1418
$p\left(R^2 = 1\right)$	0.0109	0.0059	0.0083	0.0146	0.0160	0.0252	0.0193	0.0151
MAPE	2.769%	2.734%	2.766%	2.598%	2.655%	2.068%	1.778%	2.231%
$u_t(3)$								
$\lambda_{0,j}$	1.1732	1.2312	0.8545	0.1514	0.2802	0.3314	0.6530	0.3255
	(4.7428)	(4.0781)	(3.9143)	(0.5900)	(1.1628)	(1.3229)	(2.8758)	(1.2899)
λ_j	0.4962	0.4942	0.1928	-0.6164	-0.5248	-0.6341	-0.4846	-0.6781
	(2.1715)	(1.5993)	(0.6912)	(-2.5972)	(-2.5241)	(-3.4662)	(-3.3262)	(-3.3478)
price of risk	1.402%	1.158%	0.452%	-1.397%	-1.492%	-2.647%	-2.788%	-2.376%
R^2	14.329%	9.775%	1.487%	14.221%	16.238%	51.061%	56.667%	41.156%
$se(\widehat{R^2})$	0.1086	0.1116	0.0436	0.0661	0.1091	0.1477	0.1823	0.1465
$p\left(R^2 = 1\right)$	0.0068	0.0065	0.0085	0.0150	0.0153	0.0226	0.0169	0.0137
MAPE	2.469%	2.675%	2.753%	2.628%	2.598%	2.062%	1.835%	2.190%
$u_t(12)$								
$\lambda_{0,j}$	0.8234	1.1336	0.9077	0.1657	0.2497	0.4047	0.6946	0.3887
	(3.4519)	(4.2409)	(4.1396)	(0.6456)	(0.9956)	(1.6534)	(3.0863)	(1.5558)
λ_j	0.0736	0.1906	0.1156	-0.2907	-0.3349	-0.3806	-0.2926	-0.4199
	(0.5681)	(1.5413)	(0.9401)	(-2.6401)	(-2.8365)	(-3.4100)	(-3.1887)	(-3.3174)
price of risk	0.317%	1.119%	0.636%	-1.462%	-1.779%	-2.662%	-2.735%	-2.499%
R^2	0.733%	9.132%	2.953%	15.590%	23.064%	51.640%	54.525%	45.510%
$se(\widehat{R^2})$	0.0275	0.1087	0.0627	0.0786	0.1244	0.1522	0.1882	0.1547
$p\left(R^2 = 1\right)$	0.0097	0.0061	0.0079	0.0149	0.0145	0.0184	0.0103	0.0110
MAPE	2.783%	2.682%	2.702%	2.626%	2.469%	2.050%	1.915%	2.083%
# observ.	472							

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,j}$) and the price of risk (λ_j) for each scale j along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I normalize the scale-wise risk exposures and estimate the price of risk per unit of cross-sectional standard deviation in exposure in percent per year. I also report the sample R^2 for each cross-sectional regression and its standard error, the p-value for the Kan et al. (2013) test of $H_0: R^2 = 1$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year.

Table IA.4: Cross-sectional regression with the same burn-in period: 25 FF size and variance portfolios

	Persistence level							
$j =$	1	2	3	4	5	6	7	6:7
$u_t\,(1)$								
$\lambda_{0,j}$	0.9154	0.9365	0.9270	0.8118	0.9052	0.2634	0.7476	-0.1131
	(3.6746)	(4.6809)	(5.0342)	(3.8169)	(4.2425)	(1.0479)	(2.9177)	(-0.3569)
λ_j	0.2279	0.2043	0.2387	0.0327	0.1234	-0.6392	-0.3932	-1.2460
	(0.3501)	(0.4984)	(0.5191)	(0.0938)	(0.4158)	(-3.5242)	(-1.9058)	(-5.3519)
price of risk	0.365%	0.553%	0.565%	0.104%	0.484%	-2.249%	-2.054%	-2.908%
R^2	0.862%	1.987%	2.073%	0.070%	1.520%	32.819%	27.355%	54.840%
$se(\widehat{\mathrm{R}^2})$	0.0482	0.0706	0.0700	0.0150	0.0721	0.2250	0.1976	0.1644
$p\left(\mathrm{R}^2 = 1\right)$	0.0051	0.0033	0.0038	0.0036	0.0032	0.0265	0.0004	0.0721
MAPE	3.085%	3.051%	3.050%	3.049%	3.066%	2.070%	2.595%	1.827%
$u_t\,(3)$								
$\lambda_{0,j}$	0.8213	0.8958	0.9153	0.8214	0.8640	0.2947	0.7602	-0.0194
	(3.5579)	(4.4027)	(4.8013)	(3.8130)	(4.0972)	(1.1756)	(3.0352)	(-0.0624)
λ_j	0.0360	0.0949	0.1572	0.0375	0.0834	-0.6735	-0.4439	-1.2545
	(0.1072)	(0.3554)	(0.4577)	(0.1228)	(0.2796)	(-3.5781)	(-2.0740)	(-5.1685)
price of risk	0.117%	0.393%	0.512%	0.138%	0.321%	-2.278%	-2.186%	-2.918%
R^2	0.089%	1.003%	1.702%	0.123%	0.670%	33.656%	30.986%	55.231%
$se(\widehat{\mathrm{R}^2})$	0.0161	0.0507	0.0666	0.0202	0.0484	0.2260	0.1940	0.1699
$p\left(\mathrm{R}^2 = 1\right)$	0.0050	0.0045	0.0043	0.0040	0.0032	0.0271	0.0022	0.0711
MAPE	3.051%	3.058%	3.058%	3.054%	3.068%	2.054%	2.468%	1.832%
$u_t\,(12)$								
$\lambda_{0,j}$	0.7329	0.8848	0.9180	0.7619	0.7181	0.3502	0.8178	0.1788
	(4.2543)	(4.5921)	(4.7806)	(3.5566)	(3.4867)	(1.3298)	(3.5698)	(0.5214)
λ_j	-0.0279	0.0405	0.0711	-0.0099	-0.0390	-0.4407	-0.2151	-0.7293
	(-0.1798)	(0.3420)	(0.4655)	(-0.0693)	(-0.2384)	(-3.9382)	(-1.7500)	(-4.0420)
price of risk	-0.172%	0.380%	0.521%	-0.076%	-0.254%	-2.460%	-1.987%	-3.067%
R^2	0.193%	0.935%	1.763%	0.038%	0.419%	39.255%	25.623%	61.006%
$se(\widehat{\mathrm{R}^2})$	0.0218	0.0493	0.0678	0.0114	0.0379	0.2201	0.2107	0.1278
$p\left(\mathrm{R}^2 = 1\right)$	0.0064	0.0045	0.0043	0.0039	0.0038	0.0314	0.0004	0.0694
MAPE	2.994%	3.062%	3.061%	3.017%	2.978%	1.980%	2.654%	1.775%
# observ.	472							

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,j}$) and the price of risk (λ_j) for each scale j along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I normalize the scale-wise risk exposures and estimate the price of risk per unit of cross-sectional standard deviation in exposure in percent per year. I also report the sample R^2 for each cross-sectional regression and its standard error, the p-value for the Kan et al. (2013) test of $H_0: R^2 = 1$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year.

Table IA.5: Cross-sectional regressions for $\Delta u_t^{(>7)}$

Panel A	25 FF size and book-to-market							
	$\lambda_{0,>7}$		$\lambda_{>7}$		R^2	$p\left(R^2=1\right)$	MAPE	# observ.
$h=1$	0.7020	(2.4547)	-0.0024	(-0.0247)	0.004%	0.0161	2.045%	
$h=3$	0.6924	(2.4338)	-0.0134	(-0.1271)	0.093%	0.0167	2.062%	507
$h=12$	0.6929	(2.5010)	-0.0084	(-0.1394)	0.113%	0.0166	2.065%	
Panel B	**25 FF size and investment**							
	$\lambda_{0,>7}$		$\lambda_{>7}$		R^2	$p\left(R^2=1\right)$	MAPE	# observ.
$h=1$	0.8998	(3.2180)	0.1006	(1.2163)	10.069%	0.0038	1.924%	
$h=3$	0.8926	(3.2023)	0.1019	(1.1443)	8.796%	0.0037	1.953%	472
$h=12$	0.8840	(3.1762)	0.0591	(1.0594)	8.341%	0.0033	1.966%	
Panel C	**25 FF book-to-market and operating profitability**							
	$\lambda_{0,>7}$		$\lambda_{>7}$		R^2	$p\left(R^2=1\right)$	MAPE	# observ.
$h=1$	0.4956	(2.1311)	-0.1931	(-3.6946)	21.244%	0.0115	2.771%	
$h=3$	0.4930	(2.1200)	-0.2159	(-3.7853)	22.855%	0.0123	2.755%	472
$h=12$	0.5106	(2.2299)	-0.1226	(-3.8924)	19.293%	0.0144	2.877%	
Panel D	**25 FF size and variance**							
	$\lambda_{0,>7}$		$\lambda_{>7}$		R^2	$p\left(R^2=1\right)$	MAPE	# observ.
$h=1$	0.6619	(2.2730)	-0.1396	(-1.7127)	19.577%	0.0076	3.002%	
$h=3$	0.6609	(2.2712)	-0.1540	(-1.7347)	20.171%	0.0077	2.997%	472
$h=12$	0.6833	(2.3682)	-0.0802	(-1.4883)	14.338%	0.0062	3.093%	

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,>7}$) and the price of risk ($\lambda_{>7}$) for low-frequency uncertainty shocks with persistence greater than $2^7 = 128$ months (i.e. the priced factor is $\Delta u_t^{(>7)}$) along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I report the sample R^2 for each cross-sectional regression, the p-value for the Kan et al. (2013) test of H_0 : $R^2 = 1$ denoted as $p\left(R^2=1\right)$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.6: Cross-sectional regressions for $\Delta u_t^{(8)}$

Panel A	25 FF size and book-to-market							
	$\lambda_{0,8}$		λ_8		R^2	$se(\widehat{R^2})$	MAPE	# observ.
$h=1$	0.7397	(2.5555)	-0.0618	(-0.6243)	2.627%	0.0847	2.066%	
$h=3$	0.7353	(2.5534)	-0.0768	(-0.7041)	3.349%	0.0945	2.072%	379
$h=12$	0.7475	(2.6676)	-0.0452	(-0.6743)	3.229%	0.0947	2.073%	
Panel B	**25 FF size and investment**							
	$\lambda_{0,8}$		λ_8		R^2	$se(\widehat{R^2})$	MAPE	# observ.
$h=1$	0.7967	(2.7041)	0.0052	(0.0639)	0.052%	0.0169	1.738%	
$h=3$	0.7947	(2.7136)	0.0023	(0.0266)	0.009%	0.0069	1.744%	344
$h=12$	0.7930	(2.7643)	-0.0007	(-0.0120)	0.002%	0.0032	1.750%	
Panel C	**25 FF book-to-market and operating profitability**							
	$\lambda_{0,8}$		λ_8		R^2	$se(\widehat{R^2})$	MAPE	# observ.
$h=1$	0.6304	(2.3098)	-0.1498	(-2.3513)	16.211%	0.1149	2.110%	
$h=3$	0.6333	(2.3181)	-0.1692	(-2.3330)	17.401%	0.1215	2.088%	344
$h=12$	0.6565	(2.4148)	-0.1025	(-2.2238)	14.739%	0.1116	2.136%	
Panel D	**25 FF size and variance**							
	$\lambda_{0,8}$		λ_8		R^2	$se(\widehat{R^2})$	MAPE	# observ.
$h=1$	0.7003	(2.3065)	-0.1446	(-1.6947)	41.160%	0.3077	2.120%	
$h=3$	0.7048	(2.3359)	-0.1591	(-1.7022)	42.254%	0.3104	2.102%	344
$h=12$	0.7299	(2.4950)	-0.0945	(-1.6421)	39.579%	0.3084	2.145%	

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,8}$) and the price of risk (λ_8) for low-frequency uncertainty shocks with persistence ranging between 128 and 256 months (i.e. the priced factor is $\Delta u_t^{(8)}$) along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I report the sample R^2 for each cross-sectional regression, its standard error and the mean absolute pricing error (MAPE) across all securities expressed in percent per year. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.7: $\Delta u_t^{(>7)}$ and $\Delta u_t^{(8)}$: Confidence intervals for R^2

	$h=1$		$h=3$		$h=12$	
	$\Delta u_t^{(>7)}$	$\Delta u_t^{(8)}$	$\Delta u_t^{(>7)}$	$\Delta u_t^{(8)}$	$\Delta u_t^{(>7)}$	$\Delta u_t^{(8)}$
Panel A						
R^2	0.004%	2.627%	0.093%	3.349%	0.113%	3.229%
$se(\widehat{R^2})$	0.0031	0.0847	0.0157	0.0945	0.0173	0.0947
2.5% CI (R^2)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
97.5% CI (R^2)	0.0238	0.2065	0.0449	0.2308	0.0473	0.2214
Panel B						
R^2	10.069%	0.052%	8.796%	0.009%	8.341%	0.002%
$se(\widehat{R^2})$	0.1513	0.0169	0.1417	0.0069	0.1458	0.0032
2.5% CI (R^2)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
97.5% CI (R^2)	0.3997	0.0405	0.3748	0.0230	0.3906	0.0259
Panel C						
R^2	21.244%	16.211%	22.855%	17.401%	19.293%	14.739%
$se(\widehat{R^2})$	0.0845	0.1149	0.0840	0.1215	0.0815	0.1116
2.5% CI (R^2)	0.0496	0.0000	0.0763	0.0000	0.0378	0.0000
97.5% CI (R^2)	0.3935	0.3987	0.4013	0.4121	0.3567	0.3863
Panel D						
R^2	19.577%	41.160%	20.171%	42.254%	14.338%	39.579%
$se(\widehat{R^2})$	0.2069	0.3077	0.2093	0.3104	0.1826	0.3084
2.5% CI (R^2)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
97.5% CI (R^2)	0.6080	1.0000	0.6640	1.0000	0.5488	1.0000

Notes: This table reports the sample cross-sectional R^2, its standard error and its 95% confidence interval for low-frequency uncertainty shocks with persistence greater than $2^7 = 128$ months (i.e. the priced factor is $\Delta u_t^{(>7)}$) and for low-frequency uncertainty shocks with persistence ranging between 128 and 256 months (i.e. the priced factor is $\Delta u_t^{(8)}$). I calculate the confidence interval for the sample R^2 by pivoting the cdf. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.8: Cross-sectional regressions for $\Delta IPVOL_t^{(>5)}$

Panel A	25 FF size and book-to-market							
Innovations from:	λ_0		$\lambda_{\Delta IPVOL_t^{(>5)}}$		R^2	$se(\widehat{R^2})$	$p\left(R^2=1\right)$	MAPE
First-Differences	0.0989	(0.3886)	-0.0281	(-2.1067)	20.022%	0.2039	0.0114	1.782%
			95% Confidence Interval for R^2:		[0.0000, 0.6240]			
Residuals - AR(1)	0.0262	(0.1022)	-0.0302	(-2.3703)	20.165%	0.1812	0.0129	1.837%
			95% Confidence Interval for R^2:		[0.0000, 0.5975]			
Panel B	**25 FF size and investment**							
Innovations from:	λ_0		$\lambda_{\Delta IPVOL_t^{(>5)}}$		R^2	$se(\widehat{R^2})$	$p\left(R^2=1\right)$	MAPE
First-Differences	0.1757	(0.6162)	-0.0207	(-1.4589)	15.591%	0.2071	0.0004	1.761%
			95% Confidence Interval for R^2:		[0.0000, 0.5743]			
Residuals - AR(1)	0.1306	(0.4391)	-0.0218	(-1.5254)	15.104%	0.1932	0.0004	1.766%
			95% Confidence Interval for R^2:		[0.0000, 0.5267]			
Panel C	**25 FF book-to-market and operating profitability**							
Innovations from:	λ_0		$\lambda_{\Delta IPVOL_t^{(>5)}}$		R^2	$se(\widehat{R^2})$	$p\left(R^2=1\right)$	MAPE
First-Differences	0.2435	(1.1145)	-0.0150	(-1.8551)	9.399%	0.1077	0.0160	2.393%
			95% Confidence Interval for R^2:		[0.0000, 0.3134]			
Residuals - AR(1)	0.2522	(1.1398)	-0.0139	(-1.7847)	8.268%	0.1008	0.0152	2.425%
			95% Confidence Interval for R^2:		[0.0000, 0.2954]			
Panel D	**25 FF size and variance**							
Innovations from:	λ_0		$\lambda_{\Delta IPVOL_t^{(>5)}}$		R^2	$se(\widehat{R^2})$	$p\left(R^2=1\right)$	MAPE
First-Differences	0.7049	(3.0789)	0.0019	(0.1511)	0.161%	0.0210	0.0019	2.986%
			95% Confidence Interval for R^2:		[0.0000, 0.0533]			
Residuals - AR(1)	0.7364	(2.9672)	0.0031	(0.2282)	0.363%	0.0338	0.0018	2.987%
			95% Confidence Interval for R^2:		[0.0000, 0.0750]			

Notes: This table reports the estimates for the zero-beta excess return (λ_0) and the price of risk $\left(\lambda_{\Delta IPVOL_t^{(>5)}}\right)$ for the innovations in macro volatility shocks with persistence greater than 32 months (i.e. the priced factor is $\Delta IPVOL_t^{(>5)}$ - see Boons and Tamoni, 2015) along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I report the sample R^2 for each cross-sectional regression, its standard error, the p-value for the Kan et al. (2013) test of $H_0 : R^2 = 1$ denoted as $p\left(R^2=1\right)$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.9: Cross-sectional regression with the same burn-in period: 25 FF size and book-to-market *plus* 5 FF industry portfolios

	Persistence level							
$j =$	1	2	3	4	5	6	7	6:7
$u_t\,(1)$								
$\lambda_{0,j}$	0.6482	0.7162	0.9796	0.4788	0.3493	0.3922	0.7021	0.3296
	(2.5666)	(2.8093)	(4.1880)	(2.0995)	(1.5397)	(1.6921)	(2.9600)	(1.3127)
λ_j	-0.2164	-0.0775	0.3776	-0.3953	-0.4921	-0.4921	-0.3362	-0.6293
	(-0.4406)	(-0.1959)	(0.8865)	(-1.4694)	(-2.1747)	(-3.3567)	(-2.8454)	(-3.7462)
price of risk	-0.339%	-0.151%	0.601%	-0.694%	-1.200%	-1.965%	-1.910%	-1.926%
R^2	1.704%	0.339%	5.359%	7.146%	21.386%	57.387%	54.205%	55.111%
$se(\widehat{\mathrm{R}^2})$	0.0700	0.0308	0.1018	0.1060	0.1682	0.1909	0.2482	0.1372
$p\left(\mathrm{R}^2 = 1\right)$	0.0270	0.0281	0.0261	0.0213	0.0313	0.1596	0.1543	0.1734
MAPE	2.084%	2.121%	2.150%	1.973%	1.753%	1.322%	1.538%	1.473%
$u_t\,(3)$								
$\lambda_{0,j}$	0.6248	0.7137	0.8959	0.4438	0.3238	0.4143	0.7150	0.3610
	(2.3068)	(2.5563)	(3.5530)	(1.8558)	(1.4082)	(1.7974)	(3.0474)	(1.4586)
λ_j	-0.1413	-0.0513	0.1604	-0.3776	-0.5307	-0.5197	-0.3582	-0.6568
	(-0.4820)	(-0.1813)	(0.4486)	(-1.3429)	(-2.2648)	(-3.3699)	(-2.9894)	(-3.7292)
price of risk	-0.391%	-0.144%	0.333%	-0.728%	-1.315%	-1.988%	-1.983%	-1.970%
R^2	2.273%	0.308%	1.647%	7.876%	25.709%	58.707%	58.399%	57.682%
$se(\widehat{\mathrm{R}^2})$	0.0859	0.0302	0.0645	0.1233	0.1907	0.1921	0.2323	0.1402
$p\left(\mathrm{R}^2 = 1\right)$	0.0292	0.0302	0.0319	0.0157	0.0332	0.1690	0.1421	0.1879
MAPE	2.050%	2.125%	2.183%	1.946%	1.688%	1.297%	1.475%	1.431%
$u_t\,(12)$								
$\lambda_{0,j}$	0.6406	0.7509	0.9050	0.3587	0.2903	0.4672	0.7605	0.4553
	(2.6388)	(2.8272)	(3.5765)	(1.4524)	(1.2512)	(2.0195)	(3.2917)	(1.8065)
λ_j	-0.0780	-0.0088	0.0764	-0.2269	-0.3300	-0.3200	-0.1856	-0.3741
	(-0.4964)	(-0.0723)	(0.4799)	(-1.6604)	(-2.6141)	(-3.5016)	(-2.4855)	(-3.5451)
price of risk	-0.365%	-0.060%	0.358%	-0.967%	-1.574%	-2.041%	-1.768%	-1.956%
R^2	1.985%	0.054%	1.904%	13.883%	36.831%	61.861%	46.449%	56.873%
$se(\widehat{\mathrm{R}^2})$	0.0721	0.0133	0.0698	0.1644	0.2122	0.1778	0.2634	0.1683
$p\left(\mathrm{R}^2 = 1\right)$	0.0307	0.0314	0.0319	0.0192	0.0596	0.2026	0.1175	0.1733
MAPE	2.071%	2.143%	2.180%	1.825%	1.570%	1.272%	1.641%	1.444%
# observ.	507							

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,j}$) and the price of risk (λ_j) for each scale j along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. In addition, I normalize the scale-wise risk exposures and estimate the price of risk per unit of cross-sectional standard deviation in exposure in percent per year. I also report the sample R^2 for each cross-sectional regression and its standard error, the p-value for the Kan et al. (2013) test of $H_0: R^2 = 1$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year.

Table IA.10: Controlling for Fama-French factors

	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	$\lambda_{6:7}$	R^2 / MAPE
Panel A							
$h = 1$	0.1881	0.1328	0.1693	0.2887	0.0536	-0.5001	85.546%
	(0.8549)	(0.9324)	(1.1591)	(1.5571)	(0.2033)	(-3.8181)	0.964%
$h = 3$	0.2141	0.1229	0.1577	0.2904	0.0385	-0.5288	85.668%
	(0.9828)	(0.8560)	(1.0689)	(1.5777)	(0.1443)	(-3.7145)	0.980%
$h = 12$	0.2521	0.1311	0.1021	0.2558	0.0081	-0.3484	86.244%
	(1.1774)	(0.9198)	(0.6750)	(1.3930)	(0.0302)	(-3.9708)	0.960%
Panel B							
$h = 1$	0.1354	0.2019	-0.6788	0.5167	0.1285	-0.8351	85.287%
	(0.5845)	(1.3718)	(-2.2638)	(2.8650)	(1.1421)	(-5.1764)	0.726%
$h = 3$	0.1761	0.1879	-0.7213	0.5301	0.1070	-0.8908	85.448%
	(0.7704)	(1.2683)	(-2.3959)	(2.9311)	(0.9240)	(-5.1083)	0.730%
$h = 12$	0.2713	0.2413	-0.7833	0.4967	0.0670	-0.5324	86.016%
	(1.2165)	(1.6391)	(-2.5874)	(2.7704)	(0.5461)	(-4.9612)	0.738%
Panel C							
$h = 1$	0.5365	1.2004	0.2846	0.5571	0.1401	0.2086	96.375%
	(2.3269)	(2.9695)	(1.7329)	(3.8878)	(0.6948)	(1.2954)	0.760%
$h = 3$	0.5314	1.2170	0.2955	0.5578	0.1552	0.2370	96.437%
	(2.3232)	(2.9869)	(1.7752)	(3.8928)	(0.7597)	(1.3382)	0.753%
$h = 12$	0.5064	1.1675	0.3099	0.5570	0.1571	0.1371	96.280%
	(2.2504)	(2.9350)	(1.7964)	(3.8854)	(0.7569)	(1.2358)	0.757%
Panel D							
$h = 1$	0.0380	0.0688	-0.6081	1.0639	-0.9212	-0.9560	96.508%
	(0.1689)	(0.4504)	(-2.1305)	(5.7040)	(-3.5735)	(-7.3772)	0.787%
$h = 3$	0.0891	0.0428	-0.5974	1.0479	-0.9302	-1.0085	96.548%
	(0.3989)	(0.2791)	(-2.0749)	(5.6347)	(-3.6090)	(-7.1615)	0.859%
$h = 12$	0.2095	0.1135	-0.5872	1.0080	-0.9914	-0.5847	95.926%
	(0.9522)	(0.7475)	(-2.0085)	(5.4643)	(-3.8483)	(-6.7793)	0.919%

Notes: This table reports estimates for the price of risk ($\lambda_{6:7}$) for the *business-cycle uncertainty* factor (i.e. $u_t^{(6:7)}$) after controlling for exposure to the Fama-French factors. The control factors include the value-weight excess return on the market portfolio (MKT), the size factor (SMB, small minus big), the value factor (HML, high minus low book-to-market), the operating profitability factor (RMW, robust minus weak profitability) and the investment factor (CMA, conservative minus aggressive investment). The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.11a: Controlling for UMD, STR, LTR, LIQ and portfolio characteristics

	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{STR}	λ_{LTR}	λ_{LIQ}	$\lambda_{\log(ME)}$	$\lambda_{\log(B/M)}$	$\lambda_{6:7}$	R^2 / MAPE
Panel A											
$h=1$	0.8483	0.3581	-0.2704	2.9441	1.6270	0.2982	0.0128	0.1084	0.3373	-0.4853	89.768%
	(2.9070)	(1.1789)	(-1.0475)	(3.6185)	(1.6047)	(0.5937)	(1.7078)	(1.2886)	(2.5390)	(-2.4921)	0.762%
$h=3$	0.8621	0.3239	-0.2925	2.9541	1.6101	0.2738	0.0121	0.1023	0.3405	-0.5160	89.784%
	(2.9594)	(1.0832)	(-1.1295)	(3.6272)	(1.5896)	(0.5423)	(1.6067)	(1.2316)	(2.5679)	(-2.4652)	0.771%
$h=12$	0.8925	0.3263	-0.3818	2.9083	1.5958	0.1569	0.0093	0.1006	0.3529	-0.3553	90.812%
	(3.0708)	(1.0928)	(-1.4472)	(3.6071)	(1.5777)	(0.3058)	(1.2182)	(1.2254)	(2.6807)	(-2.7327)	0.746%
Panel B											
$h=1$	0.6637	-0.0220	-0.2501	2.3845	-1.8157	-0.5628	-0.0177	-0.0057	0.5812	-0.5666	86.993%
	(2.2317)	(-0.0959)	(-0.9503)	(3.8504)	(-2.8734)	(-1.5730)	(-2.5056)	(-0.1026)	(2.4503)	(-3.3156)	0.712%
$h=3$	0.6784	-0.0477	-0.2767	2.4009	-1.8500	-0.5796	-0.0179	-0.0103	0.5755	-0.6028	86.911%
	(2.2943)	(-0.2092)	(-1.0430)	(3.8661)	(-2.9422)	(-1.6173)	(-2.5277)	(-0.1870)	(2.4290)	(-3.2937)	0.707%
$h=12$	0.7006	-0.0397	-0.3381	2.3371	-1.7226	-0.5487	-0.0174	-0.0189	0.5489	-0.3710	86.822%
	(2.3786)	(-0.1733)	(-1.2543)	(3.8016)	(-2.7327)	(-1.5392)	(-2.4621)	(-0.3508)	(2.3012)	(-3.3926)	0.705%

Notes: This table reports estimates for the price of risk ($\lambda_{6:7}$) for the *business-cycle uncertainty* factor (i.e. $u_t^{(6:7)}$) after controlling for exposure to the value-weight excess return on the market portfolio (MKT), the size factor (SMB), the value factor (HML), the momentum factor (MOM), the short-term reversal factor (STR), the long-term reversal factor (LTR), the liquidity factor (LIQ), the log size ($\log(ME)$) and the log book-to-market ratio ($\log(B/M)$). The test assets include: the 25 FF size and book-to-market portfolios (Panel A) and the 25 FF size and investment portfolios (Panel B).

Table IA.11b: Controlling for UMD, STR, LTR, LIQ and portfolio characteristics

	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{STR}	λ_{LTR}	λ_{LIQ}	$\lambda_{\log(ME)}$	$\lambda_{\log(B/M)}$	$\lambda_{6:7}$	R^2 / MAPE
Panel C											
$h = 1$	1.3886	1.0809	1.2605	0.3707	0.0059	1.2574	-0.0076	0.3267	-0.4150	0.2726	95.786%
	(2.8506)	(2.4337)	(3.8307)	(0.7142)	(0.0100)	(3.2085)	(-0.9084)	(2.6467)	(-2.1069)	(1.5939)	0.674%
$h = 3$	1.3774	1.0710	1.2627	0.3671	0.0125	1.2581	-0.0075	0.3248	-0.4083	0.2954	95.812%
	(2.8329)	(2.4167)	(3.8157)	(0.7063)	(0.0211)	(3.2069)	(-0.8967)	(2.6331)	(-2.0891)	(1.5910)	0.669%
$h = 12$	1.3663	1.0157	1.2615	0.3750	-0.0215	1.2506	-0.0076	0.3247	-0.3887	0.1837	95.811%
	(2.8148)	(2.3580)	(3.7856)	(0.7227)	(-0.0356)	(3.1986)	(-0.8897)	(2.6286)	(-2.0369)	(1.5605)	0.677%
Panel D											
$h = 1$	0.9947	-0.2181	-0.0427	1.8470	-0.5911	-1.0475	-0.0181	-0.0287	1.3366	-0.3887	85.157%
	(2.9774)	(-0.9991)	(-0.1701)	(2.9666)	(-1.1518)	(-2.4757)	(-2.8742)	(-0.7801)	(3.5824)	(-2.5062)	1.065%
$h = 3$	1.0001	-0.2458	-0.0568	1.8261	-0.6475	-1.0840	-0.0183	-0.0363	1.3275	-0.3906	85.080%
	(2.9980)	(-1.1289)	(-0.2257)	(2.9343)	(-1.2679)	(-2.5588)	(-2.9136)	(-0.9810)	(3.5509)	(-2.3398)	1.081%
$h = 12$	1.0589	-0.2582	-0.0749	1.7541	-0.6898	-1.1317	-0.0189	-0.0430	1.3718	-0.2126	84.865%
	(3.2237)	(-1.1742)	(-0.2973)	(2.8333)	(-1.3557)	(-2.6663)	(-3.0237)	(-1.1441)	(3.7236)	(-2.0777)	1.099%

Notes: This table reports estimates for the price of risk ($\lambda_{6:7}$) for the *business-cycle uncertainty* factor (i.e. $u_t^{(6:7)}$) after controlling for exposure to the value-weight excess return on the market portfolio (MKT), the size factor (SMB), the value factor (HML), the momentum factor (MOM), the short-term reversal factor (STR), the long-term reversal factor (LTR), the liquidity factor (LIQ), the log size ($\log(ME)$) and the log book-to-market ratio ($\log(B/M)$). The test assets include: the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.12: Robustness check: Residuals from an AR(1) model fitted to $u_t^{(6:7)}$

Panel A	25 FF size and book-to-market									
	$\lambda_{0,6:7}$		$\lambda_{6:7}$		price of risk	R^2	$se(\widehat{R^2})$	$p(R^2=1)$	MAPE	# observ.
$h=1$	0.0537	(0.1916)	-0.8303	(-4.3160)	-2.272%	73.719%	0.1216	0.3107	1.120%	
$h=3$	0.1063	(0.3910)	-0.8470	(-4.2973)	-2.284%	74.497%	0.1303	0.3206	1.083%	507
$h=12$	0.2248	(0.8214)	-0.4853	(-4.0227)	-2.333%	77.775%	0.1150	0.3617	1.033%	
Panel B	**25 FF size and investment**									
	$\lambda_{0,6:7}$		$\lambda_{6:7}$		price of risk	R^2	$se(\widehat{R^2})$	$p(R^2=1)$	MAPE	# observ.
$h=1$	0.1861	(0.6624)	-0.8609	(-4.6863)	-2.208%	72.761%	0.0928	0.2473	0.994%	
$h=3$	0.2471	(0.9059)	-0.8694	(-4.6310)	-2.224%	73.841%	0.0936	0.2616	0.970%	472
$h=12$	0.3987	(1.4633)	-0.4756	(-4.5741)	-2.163%	69.816%	0.1430	0.1861	1.082%	
Panel C	**25 FF book-to-market and operating profitability**									
	$\lambda_{0,6:7}$		$\lambda_{6:7}$		price of risk	R^2	$se(\widehat{R^2})$	$p(R^2=1)$	MAPE	# observ.
$h=1$	0.2946	(1.1547)	-0.6366	(-3.3480)	-2.318%	39.183%	0.1418	0.0150	2.228%	
$h=3$	0.3213	(1.2695)	-0.6776	(-3.3437)	-2.374%	41.077%	0.1465	0.0136	2.188%	472
$h=12$	0.3853	(1.5390)	-0.4200	(-3.3149)	-2.497%	45.467%	0.1547	0.0117	2.084%	
Panel D	**25 FF size and variance**									
	$\lambda_{0,6:7}$		$\lambda_{6:7}$		price of risk	R^2	$se(\widehat{R^2})$	$p(R^2=1)$	MAPE	# observ.
$h=1$	-0.1248	(-0.3922)	-1.2524	(-5.3665)	-2.901%	54.610%	0.1630	0.0716	1.831%	
$h=3$	-0.0298	(-0.0957)	-1.2602	(-5.1802)	-2.913%	55.036%	0.1690	0.0706	1.837%	472
$h=12$	0.1720	(0.4994)	-0.7319	(-4.0418)	-3.063%	60.852%	0.1273	0.0689	1.780%	

Notes: This table reports the estimates for the zero-beta excess return ($\lambda_{0,6:7}$) and the price of risk ($\lambda_{6:7}$) for the innovations in the *business-cycle uncertainty* factor (i.e. $u_t^{(6:7)}$) along with the corresponding Fama-MacBeth (1973) test statistics in parentheses. The innovations are the residuals from an AR(1) model fitted to the factor. In addition, I report the sample R^2 for each cross-sectional regression, the p-value for the Kan et al. (2013) test of $H_0: R^2 = 1$ denoted as $p(R^2 = 1)$ and the mean absolute pricing error (MAPE) across all securities expressed in percent per year. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.13: Bias-corrected bootstrapped confidence intervals for the first-pass beta estimates

Port.	Panel A		Panel B		Panel C		Panel D	
	$\beta^{(6:7)}$	90% CI	$\beta^{(6:7)}$	90% CI	$\beta^{(6:7)}$	90% CI	$\beta^{(6:7)}$	90% CI
11	-0.3286	[-1.6027, 1.0120]	-0.8675	[-1.9345, 0.1870]	-0.1982	[-1.2600, 1.0387]	**-0.9466**	[-1.5595, -0.3810]
12	-0.7378	[-1.7181, 0.2299]	**-1.0014**	[-1.7329, -0.2513]	-0.3823	[-1.4446, 0.7233]	**-1.0397**	[-1.8286, -0.1915]
13	**-1.0207**	[-1.8518, -0.2291]	**-0.8248**	[-1.6247, -0.0670]	-0.1426	[-0.7159, 0.4913]	-0.9911	[-1.9137, 0.0305]
14	**-0.9490**	[-1.7278, -0.2357]	-0.6303	[-1.4861, 0.2202]	-0.2949	[-0.8619, 0.2911]	-0.8966	[-2.0593, 0.3862]
15	**-1.1782**	[-1.9574, -0.4303]	-0.5485	[-1.6390, 0.5995]	**-0.5698**	[-1.0627, -0.0350]	-0.4671	[-1.7534, 1.0244]
21	-0.5141	[-1.5775, 0.6269]	**-0.9057**	[-1.5789, -0.1742]	-0.4956	[-1.2812, 0.3500]	**-0.8440**	[-1.3142, -0.4496]
22	-0.7381	[-1.4826, 0.0208]	**-0.9361**	[-1.5020, -0.3696]	-0.5130	[-1.0421, 0.0346]	**-0.8386**	[-1.5425, -0.1009]
23	**-0.8648**	[-1.4052, -0.3485]	**-0.8206**	[-1.3790, -0.2605]	**-0.7192**	[-1.3226, -0.0340]	-0.7478	[-1.4718, 0.0241]
24	**-0.9221**	[-1.5378, -0.3682]	**-0.8791**	[-1.5085, -0.2627]	**-0.4553**	[-0.8676, -0.0177]	-0.7424	[-1.7635, 0.3810]
25	**-1.0029**	[-1.5739, -0.4671]	-0.2919	[-1.2129, 0.7083]	-0.4887	[-1.0455, 0.0629]	-0.5766	[-1.8003, 0.8360]
31	-0.5600	[-1.3897, 0.3336]	**-0.8393**	[-1.4075, -0.2244]	-0.7105	[-1.4017, 0.0778]	**-0.8037**	[-1.2003, -0.4840]
32	**-0.9045**	[-1.5349, -0.2718]	**-0.8773**	[-1.3146, -0.4354]	**-0.6556**	[-1.1082, -0.2134]	**-0.7994**	[-1.3110, -0.2911]
33	**-0.7760**	[-1.2942, -0.3212]	**-0.9796**	[-1.5195, -0.4053]	**-0.8639**	[-1.4533, -0.2783]	**-0.7744**	[-1.4166, -0.1084]
34	**-0.9707**	[-1.4788, -0.4748]	**-0.6984**	[-1.2806, -0.0932]	**-0.6926**	[-1.3806, -0.0011]	-0.8452	[-1.6874, 0.0775]
35	**-0.8999**	[-1.4257, -0.3849]	-0.4893	[-1.3360, 0.3395]	-0.3667	[-0.8978, 0.1341]	-0.5754	[-1.6880, 0.6378]
41	-0.4984	[-1.2933, 0.3128]	**-0.7953**	[-1.3632, -0.1944]	**-0.8006**	[-1.2247, -0.4155]	**-0.9152**	[-1.2226, -0.6508]
42	**-0.7538**	[-1.3935, -0.0875]	**-0.9537**	[-1.3890, -0.5171]	**-0.8270**	[-1.2123, -0.4275]	**-0.7400**	[-1.1413, -0.3477]
43	**-0.9759**	[-1.5840, -0.3830]	**-0.8334**	[-1.3713, -0.2435]	**-0.7247**	[-1.4072, -0.0100]	**-0.6923**	[-1.2541, -0.0906]
44	**-0.9840**	[-1.4156, -0.5527]	**-0.7393**	[-1.3485, -0.1646]	**-0.6879**	[-1.1074, -0.2504]	-0.6789	[-1.3727, 0.0934]
45	**-1.0742**	[-1.5398, -0.6118]	-0.5362	[-1.3950, 0.3350]	**-0.8108**	[-1.3952, -0.3412]	-0.7986	[-1.8772, 0.3708]
51	-0.4900	[-0.9376, 0.0447]	**-0.6866**	[-1.1940, -0.1043]	**-0.6597**	[-1.0425, -0.2343]	**-0.5785**	[-0.7678, -0.2833]
52	-0.4338	[-0.8523, 0.0256]	**-0.5334**	[-0.8745, -0.2044]	**-1.0345**	[-1.4871, -0.6401]	**-0.5307**	[-0.9657, -0.0909]
53	**-0.6023**	[-1.1265, -0.0459]	**-0.5617**	[-0.9014, -0.1779]	-0.4100	[-1.0578, 0.0742]	**-0.4467**	[-0.8131, -0.0590]
54	**-0.6590**	[-1.0403, -0.2243]	-0.4729	[-1.0086, 0.1002]	**-0.9647**	[-1.5651, -0.5452]	-0.2174	[-0.8193, 0.4297]
55	**-0.5917**	[-0.8996, -0.2459]	-0.2040	[-0.8725, 0.4780]	**-1.6050**	[-2.7376, -0.4016]	-0.4943	[-1.4090, 0.4722]

Notes: This table reports confidence intervals for the first-pass horizon-dependent betas for $u_t^{(6:7)}$ using the bias-corrected percentile method and the stationary bootstrap of Politis and Romano (1994). Bold values denote statistically significant beta estimates at a 90% confidence level. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.14: Bias-corrected bootstrapped confidence intervals for the second-pass estimates

Panel A	25 FF size and book-to-market						
	$\lambda_{0,6:7}$	95% CI	$\lambda_{6:7}$	95% CI	R^2	95% CI	# observ.
$h = 1$	0.0581	[-0.3447, 0.1431]	**-0.8315**	[-1.0849, -0.7781]	**73.891%**	[0.6144, 0.8840]	
$h = 3$	0.1109	[-0.2595, 0.2194]	**-0.8476**	[-1.1315, -0.7648]	**74.617%**	[0.6209, 0.8878]	507
$h = 12$	0.2278	[-0.1728, 0.4402]	**-0.4856**	[-0.6952, -0.4198]	**77.922%**	[0.7046, 0.8965]	
Panel B	25 FF size and investment						
	$\lambda_{0,6:7}$	95% CI	$\lambda_{6:7}$	95% CI	R^2	95% CI	# observ.
$h = 1$	0.1923	[-0.2624, 0.4702]	**-0.8591**	[-1.0715, -0.8416]	**73.006%**	[0.6990, 0.8359]	
$h = 3$	0.2531	[-0.1928, 0.5742]	**-0.8672**	[-1.1174, -0.8213]	**74.027%**	[0.7147, 0.8400]	472
$h = 12$	0.4021	[-0.0343, 0.7801]	**-0.4750**	[-0.6338, -0.4130]	**70.012%**	[0.6089, 0.8424]	
Panel C	25 FF book-to-market and operating profitability						
	$\lambda_{0,6:7}$	95% CI	$\lambda_{6:7}$	95% CI	R^2	95% CI	# observ.
$h = 1$	**0.2989**	[0.0560, 0.3808]	**-0.6375**	[-0.7816, -0.5831]	**39.300%**	[0.0196, 0.7008]	
$h = 3$	**0.3255**	[0.0964, 0.4172]	**-0.6781**	[-0.8494, -0.6176]	**41.156%**	[0.0323, 0.7001]	472
$h = 12$	**0.3887**	[0.1291, 0.5263]	**-0.4199**	[-0.5117, -0.3975]	**45.510%**	[0.1258, 0.7112]	
Panel D	25 FF size and variance						
	$\lambda_{0,6:7}$	95% CI	$\lambda_{6:7}$	95% CI	R^2	95% CI	# observ.
$h = 1$	**-0.1131**	[-0.5922, -0.0252]	**-1.2460**	[-1.7315, -1.1387]	**54.840%**	[0.3833, 0.8143]	
$h = 3$	-0.0194	[-0.5317, 0.1141]	**-1.2545**	[-1.7906, -1.1201]	**55.231%**	[0.3932, 0.8031]	472
$h = 12$	0.1788	[-0.5455, 0.5349]	**-0.7293**	[-1.0099, -0.6378]	**61.006%**	[0.5029, 0.8201]	

Notes: This table reports bootstrapped confidence intervals for the second-pass estimates using the bias-corrected percentile method. Bold values denote statistically significant estimates at a 95% confidence level. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).

Table IA.15: Bias-corrected bootstrapped confidence intervals for the scale-wise predictive regressions

	Persistence level					
$j =$	6			7		
Panel A	β_6	95% CI	90% CI	β_7	95% CI	90% CI
$u_t\,(1)$	**3.0551**	[1.4756, 6.0636]	[1.8041, 5.3278]	0.3395	[-3.1428, 5.9147]	[-2.7186, 4.8427]
$u_t\,(3)$	**2.8094**	[1.3877, 5.5145]	[1.6605, 4.8525]	0.4748	[-2.8301, 5.3620]	[-2.4174, 4.4883]
$u_t\,(12)$	**4.2765**	[2.0514, 8.2260]	[2.5017, 7.2297]	1.2757	[-3.4772, 7.7966]	[-2.8486, 6.5519]
Panel B	β_6	95% CI	90% CI	β_7	95% CI	90% CI
$u_t\,(1)$	**3.0551**	[1.7187, 7.1527]	[1.9222, 5.8410]	0.3395	[-2.6837, 5.2625]	[-2.2762, 4.4559]
$u_t\,(3)$	**2.8094**	[1.5703, 6.5430]	[1.7769, 5.3312]	0.4748	[-2.3966, 4.7325]	[-2.0368, 4.0177]
$u_t\,(12)$	**4.2765**	[2.3730, 10.1137]	[2.7444, 8.2692]	1.2757	[-2.4808, 7.7078]	[-1.8131, 6.6627]

Notes: This table reports bootstrapped confidence intervals for the scale-wise predictive regressions for $j = 6, 7$ using the bias-corrected percentile method and the stationary bootstrap of Politis and Romano (1994). In Panel A the average block size is set equal to 32 - calculated based on the Politis and White (2004) estimator. In Panel B the block size is set equal to 2^j. Bold values denote statistically significant estimates.

Table IA.16: Tails of $t/\sqrt{T}$ at various percentiles

		Horizon						
$q =$		16	32	48	64	96	128	192
$u_t\,(1)$								
$\rho = 0.9866$	**0.950**	0.2665	0.3772	0.4558	0.5057	0.6005	0.6491	0.7115
$\delta = -0.1511$	**0.975**	0.3234	0.4492	0.5383	0.6075	0.7201	0.7877	0.8277
	0.995	0.4280	0.5885	0.7028	0.8024	0.9504	1.0453	1.1008
$u_t\,(3)$								
$\rho = 0.9891$	**0.950**	0.2742	0.3939	0.4692	0.5251	0.6379	0.7058	0.7612
$\delta = -0.1853$	**0.975**	0.3310	0.4644	0.5555	0.6383	0.7588	0.8350	0.8943
	0.995	0.4292	0.7246	0.7246	0.8331	1.0020	1.0866	1.2024
$u_t\,(12)$								
$\rho = 0.9943$	**0.950**	0.2848	0.4029	0.4814	0.5615	0.6783	0.7506	0.8379
$\delta = -0.1494$	**0.975**	0.3342	0.4692	0.5901	0.6688	0.7955	0.8947	0.9854
	0.995	0.4336	0.6199	0.7600	0.8968	1.0777	1.2356	1.3408

Notes: This table reports the right-tail critical values of $t/\sqrt{T}$ at various percentiles (bold values). I simulate the distribution of $t/\sqrt{T}$ for samples of length $T = 635$. I implement 5,000 replications. The distribution depends on two nuisance parameters c and δ. The parameter $c = (\rho - 1)\,T$ measures deviations from unity in a decreasing (at rate T) neighbourhood of 1. The parameter δ measures the covariance of the innovations in Equations (IA.1) and (IA.2).

Table IA.17: Multi-scale autoregressive process estimates

	Persistence level						
$j =$	1	2	3	4	5	6	7
$h = 1$							
ρ_j	0.2705***	0.0248	-0.0400	-0.1641	-0.3935***	-0.0754	-0.1542
Half-life (years)	0.0883	-	-	-	1.9816	-	-
NW t-stat	(3.4609)	(0.2591)	(-0.3005)	(-1.1020)	(-3.6137)	(-0.4605)	(-0.9950)
HH t-stat	(3.0862)	(0.2362)	(-0.3243)	(-1.1537)	(-4.0802)	(-0.6381)	(-1.1568)
Adj.R^2 (%)	[7.323%]	[0.062%]	[0.160%]	[2.697%]	[12.705%]	[0.411%]	[2.118%]
$h = 3$							
ρ_j	0.3374***	0.1102	0.0113	-0.1616	-0.4088***	-0.0735	-0.1585
Half-life (years)	0.1063	-	-	-	2.0663	-	-
NW t-stat	(3.6730)	(0.9750)	(0.0773)	(-1.0817)	(-3.7222)	(-0.4723)	(-1.0689)
HH t-stat	(3.2867)	(0.9118)	(0.0837)	(-1.1550)	(-4.1870)	(-0.6657)	(-1.3829)
Adj.R^2 (%)	[11.398%]	[1.224%]	[0.013%]	[2.613%]	[13.780%]	[0.402%]	[2.350%]
$h = 12$							
ρ_j	0.5237***	0.2988**	0.1783	-0.0776	-0.4668***	-0.0577	-0.1410
Half-life (years)	0.1786	0.1913	-	-	2.4262	-	-
NW t-stat	(6.5071)	(2.3747)	(1.1613)	(-0.5492)	(-4.0443)	(-0.4037)	(-0.9011)
HH t-stat	(5.6739)	(2.1486)	(1.2162)	(-0.5892)	(-4.4465)	(-0.6243)	(-2.8856)
Adj.R^2 (%)	[27.443%]	[8.990%]	[3.193%]	[0.607%]	[18.844%]	[0.271%]	[2.227%]
# observations	632	628	620	604	572	508	380

Notes: This table reports the estimation results of the multi-scale autoregressive system. For each level of persistence $j \in \{1, \ldots, 7\}$ I run a regression of the uncertainty component $u_{t+2^j}^{(j)}$ on its own lagged component $u_t^{(j)}$. For each regression, the table reports OLS estimates of the regressors, Newey-West (1987) and Hansen-Hodrick (1980) corrected t-statistics with $2^j - 1$ lags in parentheses and adjusted R^2 statistics in square brackets. ***,**,* denote statistical significance at 1%, 5% and 10% level respectively. Half-lives (in years) are obtained by $HL\,(j) = (\ln(0.5) \,/\, \ln(|\rho_j|)) \times 2^j/12$.

Table IA.18: Percentage contribution to total variance

Panel A							
$u_t\,(1)$	Persistence level						
$j =$	1	2	3	4	5	6	7
$\text{Var}\left(u_t^{(j)}\right)$	0.0065	0.0184	0.0455	0.0912	0.1712	0.2289	0.1873
Lower confidence bound	0.0056	0.0153	0.0366	0.0682	0.1160	0.1451	0.0955
Upper confidence bound	0.0077	0.0225	0.0582	0.1283	0.2780	0.4142	0.5202
$u_t\,(3)$	Persistence level						
$j =$	1	2	3	4	5	6	7
$\text{Var}\left(u_t^{(j)}\right)$	0.0053	0.0154	0.0404	0.0888	0.1728	0.2357	0.1900
Lower confidence bound	0.0046	0.0128	0.0324	0.0660	0.1167	0.1485	0.0967
Upper confidence bound	0.0062	0.0188	0.0520	0.1259	0.2821	0.4305	0.5300
$u_t\,(12)$	Persistence level						
$j =$	1	2	3	4	5	6	7
$\text{Var}\left(u_t^{(j)}\right)$	0.0027	0.0086	0.0250	0.0644	0.1458	0.2288	0.2144
Lower confidence bound	0.0023	0.0070	0.0194	0.0466	0.0965	0.1449	0.1077
Upper confidence bound	0.0033	0.0108	0.0333	0.0949	0.2455	0.4150	0.6169

Panel B							
$IPVOL_t$	Persistence level						
$j =$	1	2	3	4	5	6	7
$\text{Var}\left(IPVOL_t^{(j)}\right)$	0.1801	0.1956	0.2130	0.1762	0.1144	0.0556	0.0220
Lower confidence bound	0.1611	0.1700	0.1726	0.1365	0.0804	0.0378	0.0134
Upper confidence bound	0.2027	0.2275	0.2694	0.2365	0.1758	0.0899	0.0427

Notes: Panel A presents the percentage contribution of each individual component to the total variance of the time-series for aggregate uncertainty. Panel B presents the percentage contribution of each individual component to the total variance for the volatility of industrial production. Approximate confidence intervals for the variance of the components are computed based on the Chi-squared distribution with one degree of freedom (see also - Percival, 1995).

Table IA.19: Tests of Equality of Cross-Sectional R^2's

	$h=1$		$h=3$		$h=12$	
	$\Delta u_t^{(6)}$	$\Delta u_t^{(6:7)}$	$\Delta u_t^{(6)}$	$\Delta u_t^{(6:7)}$	$\Delta u_t^{(6)}$	$\Delta u_t^{(6:7)}$
Panel A						
R^2	62.416%	73.891%	63.443%	74.617%	67.543%	77.922%
$se(\widehat{R^2})$	0.2183	0.1224	0.2211	0.1311	0.2049	0.1147
2.5% CI (R^2)	0.1803	0.5167	0.2273	0.5103	0.2984	0.5616
97.5% CI (R^2)	1.0000	0.9701	1.0000	1.0000	1.0000	1.0000
difference	-0.1148		-0.1117		-0.1038	
$p\left(R^2_{(6)} = R^2_{(6:7)}\right)$	0.4089		0.3804		0.5598	
Panel B						
R^2	68.268%	73.006%	69.186%	74.027%	72.563%	70.012%
$se(\widehat{R^2})$	0.1968	0.0922	0.1942	0.0934	0.1742	0.1424
2.5% CI (R^2)	0.3267	0.5629	0.3403	0.5836	0.4144	0.4361
97.5% CI (R^2)	1.0000	0.9265	1.0000	0.9361	1.0000	0.9728
difference	-0.0474		-0.0484		0.0255	
$p\left(R^2_{(6)} = R^2_{(6:7)}\right)$	0.8115		0.7930		0.9196	
Panel C						
R^2	50.719%	39.300%	51.061%	41.156%	51.640%	45.510%
$se(\widehat{R^2})$	0.1454	0.1418	0.1477	0.1465	0.1522	0.1547
2.5% CI (R^2)	0.2384	0.1188	0.2391	0.1198	0.2457	0.1517
97.5% CI (R^2)	0.7846	0.6689	0.8047	0.6938	0.8269	0.7596
difference	0.1142		0.0991		0.0613	
$p\left(R^2_{(6)} = R^2_{(6:7)}\right)$	0.1482		0.1515		0.1950	
Panel D						
R^2	32.819%	54.840%	33.656%	55.231%	39.255%	61.006%
$se(\widehat{R^2})$	0.2250	0.1644	0.2260	0.1699	0.2201	0.1278
2.5% CI (R^2)	0.0000	0.2588	0.0000	0.2565	0.0000	0.3677
97.5% CI (R^2)	0.7946	0.8670	0.7975	0.9318	0.8191	0.8655
difference	-0.2202		-0.2158		-0.2175	
$p\left(R^2_{(6)} = R^2_{(6:7)}\right)$	0.1119		0.1220		0.3680	

Notes: This table reports tests of equality of the cross-sectional R^2's of the two competing models based on the factors $\Delta u_t^{(6)}$ and $\Delta u_t^{(6:7)}$ which are estimated over the same period (Panel A: #observ=507, Panels B-D: #observ=472). I report the sample cross-sectional R^2 and its standard error for each model, the 95% confidence interval for R^2 which is obtained by pivoting the cdf, the difference between the R^2's and the p-value for the (normal) test of $H_0 : 0 < R^2_{(6)} = R^2_{(6:7)} < 1$ denoted as $p\left(R^2_{(6)} = R^2_{(6:7)}\right)$. The reported p-values are two-tailed p-values. The test assets include: the 25 FF size and book-to-market portfolios (Panel A), the 25 FF size and investment portfolios (Panel B), the 25 FF book-to-market and operating profitability portfolios (Panel C) and the 25 FF size and variance portfolios (Panel D).