Horizon-specific macroeconomic risks and the cross section of expected returns [*]

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Abstract

We show that decomposing macroeconomic risks across horizon is key to uncover a tight link between risk premia and the real economy. Exposure in four-year returns to innovations in macroeconomic growth and volatility with a matching half-life of over four years is priced in a wide variety of test assets. Shorter-term risks are not priced. Importantly, we show that long-term growth and volatility capture largely common risk. We then propose a single, long-term, macroeconomic risk factor which drives out standard long-run risk measures and performs similar to the Fama-French three-factor model in cross-sectional tests. Our empirical results strongly support the use of long-horizon betas to measure macroeconomic risks in asset returns.

JEL classification: E32, E44, G12

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[†]An Internet Appendix with supplementary results is included at the end of this file.

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1 Introduction

The central idea of modern macro-finance is that risk premia in asset markets reflect aggregate, macroeconomic risks, that is, the tendency of assets to underperform in bad times. When macroeconomic growth and volatility are driven by shocks with heterogeneous degrees of persistence, then risk premia will reflect the collection of compensations for exposure to these heterogeneous shocks. Thus, the challenge is not only to understand whether and which macroeconomic risk factors are priced, but also to determine at which frequency these factors operate. We take up this challenge and decompose macroeconomic risk across horizons to estimate horizon-specific prices of risk. By accounting for persistence heterogeneity, by decomposing macroeconomic variables into parts of varying persistence, we uncover a tight link between risk premia and the real economy.

To be precise, we show that long-term macroeconomic growth and volatility risks are key determinants of cross-sectional variation in expected asset returns. We measure long-term risk as exposure in four-year returns to innovations in macroeconomic growth and volatility with a half-life larger than four years. This four-year horizon is not an ad-hoc choice, but follows directly from our persistence-based decomposition of risk, which is an advantage relative to alternative approaches in, e.g., Parker and Julliard (2005), Bansal, Dittmar, Lundblad (2005), and Dew-Becker and Giglio (2014). A broad cross-section of asset returns reveals that long-term risk is priced; on the other hand, the prices of shorter-term risks are considerably smaller economically, and either insignificant or driven out by long-term risk. Quantitatively, at the individual stock-level, we estimate a price of long-term risk in quarterly returns that is economically and statistically large at 2.5% for growth and -1.6% for volatility.[1] These estimates are out-of-sample and translate to absolute Sharpe ratios ranging from about 0.3 to 0.5, which is slightly above the aggregate stock market portfolio.

We find that the pricing of long-term risk at the stock-level is robust to the inclusion of stock characteristics as well as (short- and long-term) exposures to the benchmark traded factors of the CAPM (Sharpe (1964), Lintner (1965), and Mossin (1966)) and the Fama and French (1993) three-factor model. Furthermore, we find that returns increase monotonically with pre-ranking exposure to long-term risk in portfolio sorts. A high-minus-low long-term risk spreading portfolio captures a large and significant risk premium, which we interpret as compensation for post-ranking exposure

[1] The risk-prices are annualized and per cross-sectional standard deviation in historical, stock-level exposure. In most specifications, the risk prices are significant even using the data-mining adjusted t-statistic cutoff of three suggested in Harvey et al. (2013).

to long-term risk. These results are qualitatively and quantitatively robust in portfolio-level asset pricing test, where we use as test assets a wide range of stock portfolios (sorted on size, book-to-market, long-term reversal, short-term reversal, investment, and profitability) as well as Treasury bond portfolios (sorted on maturity). In fact, a single, non-traded, long-term, macroeconomic risk factor obtains an impressive cross-sectional fit in these cross-sections of portfolios, comparable in every dimension to the Fama and French (1993) model. A simulation (in the spirit of Chan et al. (1998), Kan and Zhang (1999), and Lewellen et al. (2010)) as well as a bootstrap (in the spirit of Bryzgalova (2015)) suggest that these results are unlikely to be spurious. Furthermore, our measure of long-term growth risk drives out standard measures of long-run risk used in the literature and inspired by Bansal and Yaron (2004). Finally, we find that long-term growth and volatility share a large common component of risk that determines the bulk of cross-sectional variation in expected asset returns. The evidence is also consistent with a small, orthogonal component of risk in both growth and volatility, but these components are hard to detect in practice.

Our results contribute to the existing literature in three ways. First and foremost, we contribute to the literature on long-run risks. Bansal and Yaron (2004) argue that concerns about long-run expected growth and time-varying uncertainty about future economic prospects (i.e., volatility) drive asset prices. Early evidence demonstrates that the long-run risk model is successful in capturing aggregate stock returns and explaining cross-sectional variation in the average returns of small sets of portfolios (Parker (2001), Parker and Julliard (2005), Bansal, Dittmar, Lundblad (2005), and Hansen et al. (2008)). Our finding that only those macroeconomic fluctuations with a half-life of about four years are priced, represents a useful input for calibration of these long-run risk models. However, our proposed horizon-specific measure of risk is different. In the framework of Bansal and Yaron (2004), long-run risk is measured as exposure in single period returns to long-term growth (and volatility). We measure long-term risk, instead, as exposure in long-term returns to innovations in long-term growth (and volatility). We find that our measure of risk dominates in a horse race, which suggests that exposures in long-term returns capture fundamental macroeconomic risk (as it is perceived by investors) better than betas estimated from high frequency stock returns. Similarly, Handa et al. (1989), Kothari et al. (1995), Campbell and Viceira (2002), Cohen et al. (2009), and Kamara et al. (2014) argue in favor of exposures estimated over longer horizons than a single month or quarter, for instance, because returns may react to systematic shocks with a delay or may be contaminated by temporary mispricing.

Furthermore, as noted in Ferson et al. (2013), the existing evidence on the long-run risk model is based largely on calibration exercises and in-sample data fitting. Therefore, if long-run risk models are to ultimately be useful for practical applications, such as capital budgeting, portfolio choice, and risk measurement, their performance in a setting that uses no forward-looking data in the estimation is important. Our paper fills this gap and provides empirical support for a tight link, at the four-year horizon, between financial markets and real economy using both an out-of-sample setup and granular data. Our focus on individual stocks follows the suggestion that stock-level tests are efficient, because this cross section is broad and heterogeneous in exposures (Litzenberger and Ramaswamy (1979) and Ang et al. (2011)). That said, we ascertain that our stock-level estimates are consistent with estimates obtained from a variety of stock portfolios, which is important given that inferences from portfolio-level tests often depend critically on the chosen set of test portfolios (Ahn et al. (2009) and Lewellen et al. (2010)). In fact, we also show consistent evidence in the joint cross section of stocks and bonds, for which cross-section evidence to date is limited, as highlighted in Koijen et al. (2013).

Our second contribution lies in showing that long-term growth and volatility risk are similarly important in determining expected returns. Whereas a number of recent papers find that either growth (see, among others, Lettau and Ludvigson (2001), Malloy et al. (2009), and Savov (2011)) or volatility (see, among others, Boguth and Kuehn (2014)) determines cross-sectional return variation, we find that long-lasting fluctuations in both moments represent an important source of priced risk.

Our results for volatility bridge recent empirical evidence in Bansal et al. (2014) and Campbell et al. (2014). First, we find that exposures to volatility risk are negative for the vast majority of test assets, which is consistent with Bansal et al. (2014). In contrast, Campbell et al. (2014) find positive betas for stocks, which is quite hard to justify from the perspective of economic models of agents with a preference for early resolution of uncertainty. Second, we find that exposure to low frequency innovations in macroeconomic volatility explains a considerable amount of cross-sectional variation in average returns of various stock and bond portfolios, which is consistent with Campbell et al. (2014). In contrast, the amount of cross-sectional variation explained by the volatility risk factor in Bansal et al. (2014) is modest. We obtain these results by suitably decomposing macroeconomic volatility risk across horizons.

Lastly, we contribute to literature that studies the relation between risk and returns at alternative horizons (see, e.g., Kamara et al. (2014)), frequencies (Yu (2012) and Dew-Becker and Giglio

(2014)), or time-scales (see Bandi and Tamoni (2014)).This paper builds on the scale-based decomposition of risk proposed in Bandi and Tamoni (2014). This decomposition allows the researcher to decompose risk, as proxied by the covariance between returns and a risk factor, across scales (or, horizons). With this decomposition, simple time-series techniques and a standard linear factor setup can be used to analyze scale-specific pricing. We modify this framework to make it suitable for an out-of-sample analysis that permits the use of granular asset return data, and we use this framework to study the compensation of both growth and volatility risk, which is novel.

In all, our evidence highlights the importance of decomposing risk across horizons when connecting financial markets to the real economy. A tight link exists between long-term risk and long-term returns. This evidence is suggestively consistent with a marginal investor that has a long buy-and-hold horizon. As argued in Cohen et al. (2009), among others, the long horizon is particularly relevant for corporate managers making capital budgeting decisions, pension and endowment funds making long-term investment decisions, as well as individuals making life-cycle investment decisions.[2] In light of this evidence, we believe that asset pricing theories modelling investors with heterogeneous (and possibly stochastic) horizons, such as Beber et al. (2011) and Brennan and Zhang (2013), may prove particularly useful to understand the behavior of asset prices.

The remainder of the paper is organized as follows. In Section 2, we provide the background for the analysis of time series with multiple scales, introduce the decomposition of covariance across scales, and describe our cross-sectional regression methodology. In Section 3, we test whether exposure to macroeconomic growth risk is priced at different scales among individual stocks and a range of stock and bond portfolios. In Section 4, we analyze the scale-specific pricing of macroeconomic volatility risk and run a horse race between growth and volatility. In Section 5, we examine the robustness of our results. In Section 6, we summarize and conclude. An appendix summarizes our data sources.

[2] Actively managed equity mutual funds are traditionally considered as being shorter-term investors than other institutional investors, such as pension funds. However, recent work by Lan et al. (2015) shows that U.S.-domiciled equity mutual funds exhibit significant cross-sectional variation in investment horizons, with an average holding period of 1.21, 2.97, and 7 years, for funds with the shortest, middle, and longest horizon, respectively.

2 Methodology

In this section we discuss the methodology and data (sources). We first describe how a macroeconomic risk factor can be decomposed into components that evolve over different horizons. Next, we describe how these components can be used to estimate horizon-specific macroeconomic risk exposures as well as horizon-specific prices of risk using a standard cross-sectional asset pricing setup.

2.1 Decomposition of risk across scales

The basic premise of our analysis is that a macroeconomic risk factor, f_t, can aggregate multiple components evolving over different time scales, and these components may constitute different sources of risk. Thus, treating the components separately allows us to get a finer understanding of whether macroeconomic risk is priced in financial markets, and at which horizons precisely. Our goal is to estimate horizon-specific prices of risk for exposure to the innovation, $u_{f,t}$, in the macroeconomic factor. We are interested in the innovation, because only this unexpected part captures systematic news that constitutes risk to the investor (see, e.g., Chen et al. (1986) and Ferson and Harvey (1991)).[3] Following Chen et al. (1986) and Liu and Zhang (2008), we focus on industrial production in our main empirical analysis.[4] Thus, f_t is either industrial production growth (IPG, henceforth) or industrial production volatility (IPVOL, henceforth).

We start our analysis by decomposing the innovation, $u_{f,t}$, and the excess returns of each asset i, $R_t^{e,i}$, into components with different levels of persistence. Although alternative choices are possible, in this paper we follow the persistence-based decomposition suggested in Ortu et al. (2013) and use

[3] Our work is related to the Intertemporal CAPM of Merton (1973), where exposure to innovations in state variables command a risk premium. See, among others, Petkova (2006), Maio and Santa-Clara (2012) and Boons (2014) for empirical work.

[4] Our results are robust to alternative measures of economic activity, using consumption or (un-) employment data (see Section 5). Moreover, although we focus on macroeconomic growth and volatility, our framework is general and can be applied to investigate horizon-specific pricing of alternative risk factors, such as inflation (Chen et al. (1986)), human capital (Jagannathan and Wang (1996)), investment (Cochrane (1996)), cash-flow versus discount-rate risk (Campbell and Vuolteenaho (2004)), and systematic illiquidity (Pastor and Stambaugh (2003) and Acharya and Pedersen (2005)).

simple moving averages to extract the components of a time series. The decomposition is as follows:

$$u_{f,t} = \sum_{j=1}^{J} u_{f,t}^{(j)} + u_{f,t}^{(>J)} \ , \tag{1}$$

$$R_t^{e,i} = \sum_{j=1}^{J} R_t^{e,i,(j)} + R_t^{e,i,(>J)} \ , \tag{2}$$

where $u_{f,t}^{(>J)} = \sum_{j>J} u_{f,t}^{(j)}$, $R_t^{e,i,(>J)} = \sum_{j>J} R_t^{e,i,(j)}$, and $u_{f,t}^{(j)}$ and $R_t^{e,i,(j)}$ are components associated with time (t) and *scale* ($j = 1, ..., J$ and $j > J$).[5] Each component at scale $j = 1, ..., J$ is the difference between moving averages of sizes 2^{j-1} and 2^j. The component at scale $j > J$ is a 2^J-period moving average. We refer interested readers to Section 2.1 in Ortu et al. (2013) for a detailed exposition of the extraction method. Therefore, when quarterly data are used, the component $u_{f,t}^{(j)}$ (and, analogously, $R_t^{e,i,(j)}$) captures those fluctuations with half-life in the interval $[2^{j-1},\ 2^j)$ quarters, whereas the component $u_{f,t}^{(>J)}$ (and, analogously, $R_t^{e,i,(>J)}$) captures those fluctuations with half-life exceeding 2^J quarters.

To be able to perform out-of-sample pricing tests, where betas are estimated over an historical rolling window, we need to set a maximum level of persistence: $J = 4$, which corresponds to an horizon of four years.[6] In Table 1, we present a more detailed overview of the interpretation of the time-scale j in terms of corresponding time span.

[Insert Table 1 about here.]

Bandi and Tamoni (2014) (Section 2) show that, if the components are decimated (i.e., suitably sampled over a grid with time-steps of length 2^j periods), the covariance between the risk factor

[5] Throughout this paper, we compute the innovation at scale j, $u_{f,t}^{(j)}$, as the first-difference in the respective component of the original series f_t (that is, either IPG or IPVOL) at scale j, such that $u_{f,t}^{(j)} = \Delta f_t^{(j)}$. Fitting an auto-regressive model to the components of the original series, and using the residuals at alternative scales as our innovations, yields almost identical results. We focus on the first-difference of the components for two reasons. First, this approach is simpler, as it does not require us to estimate additional parameters. Second, using first-differences gives rise to an alternative interpretation. It is easy to show that within our decomposition, the first-difference of a component of the original series is identical to the component of the first-difference of the original series.

[6] Our main analysis uses a standard five-year rolling window to estimate horizon-specific exposures, such that it is impossible to draw any inference about the persistence of shocks that last much longer. In a robustness check (see Table IA.3) we change the data frequency to monthly and set $J = 5$. This choice is consistent with our quarterly exercise, in that the long-term component captures fluctuations with half-life larger than 32 months, or 2.7 years.

and returns can be decomposed across scales:

$$Cov\left[R_t^{e,i}, u_{f,t}\right] = \sum_{j=1}^{J} Cov\left[R_{k2^j}^{e,i,(j)}, u_{f,k2^j}^{(j)}\right], \tag{3}$$

where $R_{k2^j}^{e,i,(j)}, u_{f,k2^j}^{(j)}$ are the decimated components. Decimation can be accommodated in a portfolio-level pricing test. In contrast, decimation prevents an out-of-sample exercise at the stock-level, because a sufficiently long, unbroken series of returns is available only for a small subset of stocks.[7] Fortunately, Whitcher et al. (2000) show that the covariance-decomposition in Eq. (3) can be extended to the case where the components are not decimated,[8]

$$Cov\left[R_t^{e,i}, u_{f,t}\right] = \sum_{j=1}^{4} Cov\left[R_t^{e,i,(j)}, u_{f,t}^{(j)}\right] + Cov\left[R_t^{e,i,(>4)}, u_{f,t}^{(>4)}\right]. \tag{4}$$

Here, the last term is the covariance of the long-run trends, setting the maximum level of persistence $J = 4$. Eq. (4) forms the basis for our subsequent analysis of scale-dependent macroeconomic risk. It is important to note that the decomposition is exact asymptotically, with components that are uncorrelated across scales.[9] In-sample, though, the components are not uncorrelated across scales. We verify empirically that the cross-covariances are not important for pricing.[10] Thus, in the rest of the paper, we focus only on equal-scale covariances. This approach is consistent with previous literature that estimates covariances between horizon-matched stock and traded factor returns to analyze risk across horizons (see, e.g., Handa et al. (1989), Kothari et al. (1995), and Kamara et al. (2014)) .

Dividing Eq. (4) by the variance of $u_{f,t}$, we have that beta of the original series is a weighted

[7]Even a stock whose life spans ten years will have only two observations left after decimation (i.e. after sampling every $2^4 = 16$ quarters) to study covariance at scale $J = 4$.

[8]See Eq.(7) in Section 3.1 of Whitcher et al. (2000). See also Gencay et al. (2002, Ch. 7) for a in-depth treatment of wavelets and their use to decompose covariances on a scale by scale basis.

[9]For instance, consider two contiguous scales, j and $j + 1$. Since the extracted cycles are smooth asymptotically, component j will complete two cycles for every cycle completed by component $j + 1$. Consequently, the two scales are uncorrelated.

[10]These results are available upon request from the authors.

average of component-wise betas:

$$\frac{Cov\left[R_t^{e,i},u_{f,t}\right]}{var\left[u_{f,t}\right]}=\sum_{j=1}^{4}w_f^{(j)}\frac{Cov\left[R_t^{e,i,(j)},u_{f,t}^{(j)}\right]}{var\left[u_{f,t}^{(j)}\right]}+w_f^{(>4)}\frac{Cov\left[R_t^{e,i,(>4)},u_{f,t}^{(>4)}\right]}{var\left(u_{f,t}^{(>4)}\right]}, \text{ or} \tag{5}$$

$$\beta_{i,f}=\sum_{j=1}^{4}w_f^{(j)}\beta_{i,f}^{(j)}+w_f^{(>4)}\beta_{i,f}^{(>4)}, \tag{6}$$

where $w_f^{(j)}=var[u_{f,t}^{(j)}]/var[u_{f,t}]$ for $j=1,2,3,4,>4$. The main purpose of this decomposition is to accommodate the hypothesis that the innovation $u_{f,t}$ may look like white noise, but hide small and persistent components that represent important risk in the long run (Ortu et al. (2013)). Given their relatively high volatility, comovement between the high frequency components of returns and innovations in the macroeconomic risk factor dominates the beta of the original, raw series. Using our decomposition, we are instead able to separate the high-frequency from the low frequency components, and to ask whether the latter are more suited to measure priced risk. This hypothesis is also consistent with the common intuition that the investment horizon of the average investor is more than just a few quarters (see, e.g., Campbell and Viceira (2002) and Cohen et al. (2009)).

To summarize, we note that the horizon-specific exposures to macroeconomic risk that are the focus of our paper are defined analogously, replacing in Eq. (6) the innovation in the generic risk factor f_t with the innovation in industrial production growth ($u_{IPG,t}$, built up from components $u_{IPG,t}^{(j)}$) and volatility ($u_{IPVOL,t}$, built up from components $u_{IPVOL,t}^{(j)}$). Given that the components are backward looking, with, e.g., $u_{IPG,t}^{(>4)}$ representing the innovation in past four-year average growth, it is natural to regress them on past four-year average returns. Thus, with our choice of 2^j-period simple moving average as the filtering device, our measure of long-term risk, $\beta_i^{(>4)}$, can be conveniently interpreted as the coefficient from a long-horizon regression of returns on the long-term innovation in the factor.[11]

2.2 Horizon-specific risk exposures and pricing

To test whether horizon-specific exposures to macroeconomic risk capture cross-sectional variation in asset returns, we study a specification where the expected excess return of asset i is a linear

[11]See Section 4 in Bandi and Tamoni (2014) for a formal derivation of the link between scale-wise betas and long-horizon betas.

function of its scale-wise exposures to either growth or volatility:

$$E[R^{e,i}_{t+1}] = \lambda_0 + \sum_{j=1}^{4} \beta^{(j)}_i \lambda^{(j)} + \beta^{(>4)}_i \lambda^{(>4)} + \alpha_i \ . \tag{7}$$

Here, $\lambda^{(j)}$ is the price of risk at each scale $j = 1, ..., 4$, that is, the price of risk for exposure to macroeconomic fluctuations with half-life in the interval $[2^{j-1}, 2^j)$ quarters, and $\lambda^{(>4)}$ is the price of risk for exposure to fluctuations with half-life larger than 16 quarters. We first estimate separately the price of risk at each scale by running simple ordinary least squares (OLS) cross-sectional regressions. These restricted specifications are attractive, because they require us to estimate fewer betas for each individual stock and alleviate concerns about betas that are correlated across scales in the cross section. Next, we consider the full specification of Eq. (7) to determine which individual scale is dominant. Throughout the paper, however, our main interest is in a restricted two-factor model that separates high versus low frequency risk, inspired by the more classical separation between transitory and permanent shocks. This restricted specification combines scales $j = 1, \ldots, 4$ into one high frequency scale, denoted $j = 1 : 4$. In this case, $\beta^{(1:4)}_i$ and $\lambda^{(1:4)}$, respectively, measure exposure to and the price of risk of macroeconomic fluctuations with half-life in the interval $[1, 16)$ quarters.

Our out-of-sample stock-level exercise is inspired by the work of Fama and MacBeth (1973) and Fama and French (1992). First, we estimate time-varying scale-wise exposures for each individual stock i in the sample. We do so by running rolling quarterly OLS time-series regressions of excess returns at scale j on the respective innovation at scale j in the macroeconomic risk factor. For instance, in the case of IPG, in each quarter t^* we estimate

$$R^{e,i,(j)}_t = c^{(j)}_{i,t^*} + \beta^{(j)}_{i,t^*} u^{(j)}_{IPG,t} + \epsilon^{(j)}_{i,t} \ , \tag{8}$$

where we let $t \in \{t^* - 19, t^*\}$, such that betas for all scales j are estimated using the last five years of quarterly data.[12] Since four additional years are required as burn-in period for the moving averages in the computation of the components, we use only those assets that have at least nine

[12] A five-year window to compute long-horizon betas is also used in Kamara et al. (2014), for instance. In Table IA.2 of the Internet Appendix we vary the rolling window up to ten years and show that our results are not sensitive to the choice of the window length.

years of prior return data.[13] This biases our results towards big, old, and healthy firms, which is an advantage given that many anomalies inconsistent with the pricing of (macroeconomic) risk are driven by small, illiquid, financially distressed stocks (Avramov et al. (2013)).Second, we use these estimated exposures to run the cross-sectional regression

$$R^{e,i}_{t+1} = \lambda_{0,t} + \lambda^{(j)}_{growth,t}\ \widehat{\beta^{(j)}_{i,t}} + \alpha_{i,t+1}\ , \tag{9}$$

for each quarter in the sample. Our interest is in the horizon-dependent prices of risk, captured by the time-series average of the estimated $\lambda^{(j)}_{growth,t}$'s.

It is important to note that the components of IPG are not estimated, so that we can treat the components as observables in the first-stage time-series regression.[14] This is an advantage of our framework relative to recent work of Boguth and Kuehn (2014), who impose a model for the dynamics of consumption growth and estimate beliefs about growth and volatility, and Dew-Becker and Giglio (2014), who estimate the dynamic response of consumption growth to fundamental economic shocks using a vector auto-regression. Even so, an errors-in-variables (EIV) concern about the econometric inferences from our analysis stems from using the estimated first-stage scale-wise betas from Eq. (8) as independent variables in the second-stage cross-sectional regressions of Eq. (7).

We address this concern in three ways. First, we sort stocks into portfolios. This approach is more conservative under the null of cross-sectional predictive power, as some stocks will be assigned to the wrong portfolio (see discussion in Boguth and Kuehn (2014)). Second, we perform portfolio-level asset pricing tests. In this case, we estimate Eq. (7) by conducting an OLS cross-sectional regression of average portfolio returns on scale-wise betas that are estimated over the full sample, as it is common in the literature. This approach is attractive as it alleviates concerns about EIV relative to the exercise with individual stocks, in which out-of-sample exposures are estimated

[13] An alternative approach would be to use a burn-in specific period for each component. For instance, one could use six years for the second component (five years for beta estimation and one year for burn-in), seven years for the third component (five years for beta estimation and two years for burn-in), and so on. In this case, however, the number of firms included in the sample will vary across scales, which confounds the comparison of the horizon-specific prices of risk. Our main conclusions are qualitatively robust to this alternative method, though.

[14] Strictly speaking, the components and the scale over which they evolve do depend on the assumptions in the horizon decomposition, and in particular on the choice of the base frequency (one quarter) and the progression (multiples of 2). However, using monthly data in a robustness check we show that our results are largely consistent with the quarterly ones. This ensures that our estimate of the horizon at which the macroeconomic factor operates is not driven just by noise.

using historical data alone. In fact, by sorting stocks into portfolios, we create test assets with exposures that are more stable over time and likely measured better, because estimation error at the stock-level may cancel out inside the portfolio (see, also, Blume (1970) and Fama and MacBeth (1973)). Moreover, portfolio-level asset pricing tests allows us to draw inference on the prices of risk using generalized method of moments (GMM) standard errors (see Cochrane, 2005, Ch. 12), and, therefore, to correct for the estimation error in the first-stage horizon-specific exposures. Third, Section 3.3 conducts a small-sample simulation experiment to confirm that our results are unlikely to be spurious. In a robustness check, we adopt the penalized cross-sectional regression suggested in Bryzgalova (2015), which in combination with a bootstrap experiment further strengthens this claim.

2.3 Data

A complete description of our data sources can be found in Appendix A. Consistent with most literature on the cross-section our sample starts in 1962, which coincides with the introduction of AMEX firms in the CRSP file. We use industrial production growth (IPG) as our main measure of macroeconomic activity. This choice guards against measurement problems that are common to many macroeconomic variables, because IPG focuses on easily measured quantities in industries like manufacturing, mining, and electric and gas utilities. These are the industries, along with construction, where the bulk of business cycle variation occurs.[15] However, we show that our findings are robust to two important alternative measures: consumption growth (denoted CG) and the first principal component of industrial production, consumption, employment, and unemployment, that is, a composite measure of real activity (denoted CRAG) in the spirit of Ang and Piazzesi (2003).

To measure macroeconomic volatility, we consider an AR(1)-GARCH(1,1) specification:

$$IPG_t = \mu + \rho IPG_{t-1} + \eta_t, \tag{10}$$

$$\sigma_t^2 = \omega_0 + \omega_1 \eta_{t-1}^2 + \omega_2 \sigma_{t-1}^2. \tag{11}$$

The square root of the fitted value, σ_t^2, is our proxy for IPVOL. Our conclusions on the pricing of volatility risk are robust to using the log of volatility, which attenuates concerns about skewness

[15] See `http://www.federalreserve.gov/releases/G17/About.htm`.

and spikes in the volatility series.[16] To estimate Eqs. (10) and (11), we use the full sample spanning the third quarter of 1926 to the fourth quarter of 2011.[17] To provide out-of-sample evidence on the pricing of volatility risk (similar to the case of growth), we also perform an expanding-window estimation of the AR(1)-GARCH(1,1) specification. For this exercise, we use in each quarter t all historical IPG observations starting from the third quarter of 1926. Whenever the out-of-sample conditional volatility series is used to estimate the price of volatility risk, we denote it IPVOL-OOS.

Figures 1 and 2 show, respectively, the decomposition of quarterly IPG and IPVOL into high and low frequency risk, that is, the sum of components at scale $j = 1 : 4$ (top panel) versus the long-run components at scale $j > 4$ (bottom panel).[18] In both cases, we observe that the components are persistent, with larger persistence for the low frequency components ($IPG_t^{(j>4)}$ and $IPVOL_t^{(j>4)}$). For this reason exactly, we first-difference the components and these innovations will serve as the risk factors in our subsequent analysis.

[Insert Figures 1 and 2 about here.]

3 Macroeconomic growth risk

In this section, we investigate whether exposure to industrial production growth (IPG) risk measured over suitable scales, or horizons, can explain the cross-sectional variation of asset returns. We first present Fama and MacBeth (1973) regressions of quarterly individual stock returns on lagged scale-specific macroeconomic risk loadings. Next, we turn to portfolio-level tests. To complete our analysis of the pricing of growth risk, we also present a small sample simulation experiment and compare our scale-specific risk measures to standard measures of long-run risk inspired by Bansal and Yaron (2004). Section 5 contains a range of robustness checks for the pricing of macroeconomic growth.

[16] These results are available upon request. Our conclusions are also robust to using a measure of realized volatility following Bansal et al. (2014).

[17] Mixing pre- and post-war data may be problematic due to changes in data collection methods. Our robustness checks using post-war consumption volatility address this concern.

[18] The sum of these two components exactly reconstruct the original IPG and IPVOL series. To see this, apply Eq. (1) for $J = 4$ to obtain $f_t = \sum_{j=1}^{4} f_t^{(j)} + \sum_{j>4} f_t^{(j)}$ where f_t is either IPG or IPVOL.

3.1 Individual stock-level tests

3.1.1 Fama and MacBeth (1973) cross-sectional regressions

Panel A of Table 2 presents horizon-dependent prices of risk (with corresponding Fama and MacBeth (1973) $t-$statistics presented underneath each estimated risk-price) from stock level cross-sectional regressions of quarterly individual stock returns on pre-ranking scale-wise risk exposures (see Eqs. (8) and (9)). Throughout, the scale-wise risk exposures are normalized to have standard deviation equal to one, such that we measure the risk premium per cross-sectional standard deviation in historical exposure. The first six models in Panel A show simple regressions that estimate the individual effect at each scale $j = 1, 2, 3, 4$ as well as for the combined scales $j = 1 : 4$ (high frequency) and $j > 4$ (low frequency). Next, we present two multiple regressions that focus on the marginal predictive role of high versus low frequency risk. The first specification is a two-factor model including $j = 1 : 4$ and $j > 4$. The second specification is the full five-factor model including the risk exposures at all scales (except $j = 1 : 4$). The full model is more attractive from an economic point of view, because it provides detailed evidence on the pricing of macroeconomic growth risk at different horizons. However, this model is less attractive from an econometric point of view, because it requires us to estimate five betas for each individual stock in the sample, which increases estimation error.

[Insert Table 2 about here.]

Among the prices of risk for the high frequency scales (i.e. $j = 1, \ldots, 4$), only $j = 1$ is marginally significant. When the first four components are bundled together, the price of high frequency risk ($j = 1 : 4$) is marginally significant at 1.25%. The price of low frequency risk ($j > 4$) is twice as large at 2.50% and significant even using the data-mining adjusted t-statistic cutoff of three suggested in Harvey et al. (2013). In the multiple regressions, the price of low frequency risk $\lambda^{(>4)}$ remains large and significant using the same cutoff. The estimate equals 2.10% when we control for the combined scale-wise exposure $j = 1 : 4$, and 2.89% when we include all the scale-wise exposures $j = 1, 2, 3, 4$. In both cases, the prices of high frequency risks are considerably smaller economically and typically insignificant.

In Panel B of Table 2 we analyze whether these conclusions are robust to controlling for characteristics as well as exposure to benchmark asset pricing factors in Eq. (9). To conserve space, we focus here on the two-factor model including high and low frequency macroeconomic risk at scale $j = 1:4$ and $j > 4$, respectively. In particular, the first model in Panel B shows that the price of low frequency macroeconomic risk is robust to the inclusion of size and book-to-market at a large and significant 1.82%, to be compared with a 0.26% for high frequency risk.[19] The next two models control for exposure to market risk (MKT) and the two factors designed to capture the size and value effect in stock returns (SMB and HML, respectively).[20] The second model in Panel B controls for exposures to these factors in quarterly returns. A number of papers document that MKT and HML risk premia depend on the horizon over which beta is estimated, however (see, e.g., Bandi et al. (2011), Brennan and Zhang (2013), and Kamara et al. (2014)). To address this evidence, the third model in Panel B controls for long-term exposure to these factors in overlapping four-year returns. In short, we see that the price of low frequency risk is not captured by exposure to the benchmark traded factors.

In sum, we conclude that macroeconomic growth risk predicts returns in the cross section of individual stocks. This conclusion is driven by the fluctuations in IPG with a half-life larger than four years, as shorter-term fluctuations are not priced.

3.1.2 Portfolio Sorts

An alternative approach to use the scale-wise macroeconomic risk loadings from the regression in Eq. (8) is to form portfolios. To control for size, each of our risk-sorted quintile portfolios is the equal-weighted average of five portfolios at the intersection of a double sort into (i) NYSE market value quintiles and (ii) quintiles according to either high ($j = 1:4$) or low ($j > 4$) frequency macroeconomic risk exposure. We either equal-weight (Panel A) or value-weight (Panel B) the stocks inside each portfolio. Table 3 presents average and risk-adjusted returns, standard deviations, Sharpe ratios, and post-ranking betas for these portfolios. To conserve space, the table reports the results only for quintile one (High), three, and five (Low) as well as for the High-minus-Low spreading portfolio.

[Insert Table 3 about here.]

[19] Following Chordia et al. (2012), size is the natural logarithm of market capitalization and book-to-market is the natural logarithm of the book-to-market ratio winsorized at the 0.5th fractile. Both characteristics are standardized cross-sectionally.

[20] These benchmark exposures are estimated over a five-year rolling window, as is standard in the literature.

First, we see that returns increase monotonically in exposure to low frequency macroeconomic risk (columns five to eight), but not high frequency risk (columns one to four). The resulting High-minus-Low average return spread is large and significant only for low frequency risk at 5.55% ($t = 3.63$), when stocks are equal-weighted, and 5.03% ($t = 3.14$), when stocks are value-weighted. These risk-prices translate to Sharpe ratios of about 0.50 for low frequency risk, which is large relative to about 0.15 for high frequency risk and 0.30 for the aggregate stock market portfolio.

Finally, in Panel C we report equal-weighted average characteristics within the quintile portfolios, that is, pre-ranking beta, market share, and book-to-market. Consistent with Panel B of Table 2, we find that stocks with high exposures to low frequency risk are not dramatically different from low exposure stocks in terms of size and book-to-market. Further, the pre-ranking exposures in Panel C demonstrate that there exists stocks across a wide spectrum of exposures to both high and low frequency risk. As is common in the literature with non-traded factors, however, these exposures are measured with noise, such that the post-ranking betas reported in Panels A and B are smaller. Importantly, the post-ranking exposures are significant within each quintile and positive for the High-minus-Low spreading portfolios.[21]

3.2 Portfolio-level tests

In this section, we study the pricing of high and low frequency macroeconomic growth risk at the portfolio-level. Because estimates of risk premia are known to be sensitive to the choice of test portfolios (see, e.g., Daniel and Titman, (1997), Kan and Zhang (1999), and Lewellen et al. (2010)), we consider three separate cross sections of portfolios. Our first set of portfolios is standard: the 25 size and book-to-market portfolios of Fama and French (1993). Second, we analyze a joint cross section of eleven stock and bond portfolios following Koijen et al. (2013), including the CRSP value-weighted market portfolio, five value-weighted book-to-market portfolios, and five constant maturity Treasury bonds with maturities of one, two, five, seven, and ten years. General equilibrium models link both sets of returns to macroeconomic quantities, whereas joint empirical evidence is still limited. Third, we consider a set of 30 portfolios, consisting of five portfolios sorted on either size, book-to-market, long-term reversal, short-term reversal, investment, or profitability. We hope

[21]Note that the average return spreads in Panels A and B are consistent in magnitude with the cross-sectional regression estimates in Table 2. To see this, we note that the High-minus-Low difference in pre-ranking beta is about 2.5 standard deviations for low frequency risk. Combined with the price of risk in Panel A of Table 2, this difference implies a predicted High-minus-Low average return spread of about 6.25% (= 2.50% $\times$ 2.5).

to create a level playing field for high and low frequency variation in macroeconomic risk by including portfolios sorted on short- and long-term past returns as well as on additional characteristics recently linked to stock returns (see Fama and French (2015) and Hou et al. (2014)).

3.2.1 Exposures

Table 4 presents the first-stage full sample component-wise betas of the portfolios with respect to innovations in the components of IPG, $u^{(j)}_{IPG,t}$. For all three sets of portfolios, we see that long-run betas at scale $j > 4$ are larger in magnitude than those at scale $j = 1 : 4$. To grasp the economic magnitude of these exposures, we note that the low frequency betas of 2.53, 3.41, and 1.55 for the market, value (high book-to-market quintile), and 10-year Treasury bond portfolio imply that the four-year average return of these portfolios increases by 0.22, 0.29 and 0.22 standard deviations, respectively, when $u^{(>4)}_{IPG,t}$ increases by one standard deviation. These per-standard-deviation exposures are considerably smaller for high frequency risk: a one-standard deviation increase in $u^{(1:4)}_{IPG,t}$ implies a change of 0.12, 0.16 and -0.14 (in units of standard deviation) in the component of returns at scale $j = 1 : 4$. In both cases, however, the betas are typically significant individually. Thus, the portfolios in these three cross sections are exposed to both high and low frequency macroeconomic risk, which suggests that these macroeconomic factors are not useless in the sense of Kan and Zhang (1999) and Kleibergen and Zhan (2013). We conclude that these cross sections are well-suited for the asset pricing test.

[Insert Table 4 about here.]

Next, we analyze the cross-sectional pattern in these exposures. Both high and low frequency betas ($\beta^{(1:4)}$ and $\beta^{(>4)}$) are decreasing in size, just like average returns. In contrast, only low frequency betas are increasing in book-to-market, a pattern also consistent with average returns. Bond returns also demonstrate an important difference between high and low frequency risk exposures. High frequency betas are negative for all five bonds and decreasing in maturity. This pattern is inconsistent with the fact that bonds have positive average returns that are increasing in maturity. In contrast, low frequency betas are increasing in bond maturity. Moreover, the exposures in bond returns to low frequency risk are all positive and smaller than stock exposures, consistent with a positive difference between average stock and bond returns. Finally, we observe that low frequency betas increase in profitability, but decrease in long-term return, short-term return, and investment. In all cases, this pattern is consistent with average returns. High frequency betas move in the same direction, but the pattern is less pronounced. In conclusion, this evidence suggests that low frequency macroeconomic growth risk should adequately explain cross-sectional variation in the average returns of these portfolios, at least relative to high frequency risk. In the following, we directly test this hypothesis and quantify the premia associated with these scale-specific risks.

3.2.2 Cross-sectional regressions

Table 5 presents OLS cross-sectional regressions that analyze the pricing of macroeconomic risk at different scales for the three sets of portfolios of interest (in Panel A, B, and C, respectively). As in Table 2, the cross section of exposures is normalized to have standard deviation equal to one. In general terms, a macroeconomic model performs well if it obtains in each cross section (i) a good cross-sectional fit (large R^2 and small Mean Absolute Pricing Error (MAPE)), (ii) a price of macroeconomic growth risk that is significantly positive and robust, and (iii) an intercept that is small and insignificant. The standard errors of the estimated prices of risk are computed closely following the GMM-approach of Cochrane (2005, Ch. 12), and, thus, they account for heteroskedasticity and the estimation uncertainty in the betas.[22]

[Insert Table 5 about here.]

First, consistent with theory and intuition, we see that the estimated prices of short- and long-term macroeconomic growth risk are all positive. However, the best fit is obtained when risk exposure is measured at the low frequency ($j > 4$). Indeed, this model obtains the largest R^2 among all the single-factor models at 0.693, 0.906 and 0.643 in Panel A, B, and C, respectively. In addition, in this model the price of low frequency macroeconomic risk is large, both economically and statistically, at 2.42%, 2.66% and 1.66%, respectively, whereas the intercept is insignificant. In comparison, the price of risk at the high frequency ($j = 1 : 4$) is typically smaller, with a poorer cross-sectional fit (R^2) and significantly positive intercepts. In all, low frequency macroeconomic risk is an adequate and robust predictor of average returns in each cross-section. Indeed, in the joint regressions, short-term risk ($j = 1 : 4$) is driven out by long-term risk ($j > 4$), and this two-factor model obtains a cross-sectional fit that is similar to that of the single-factor model with $j > 4$.

[22]We consider no lags of the moment functions when estimating these standard errors. As stressed in Cochrane (2005, Ch. 12): if the asset pricing model is true, then the moments that define the pricing errors will be orthogonal to all past information, including the past pricing errors.

A comparison with the benchmark three-factor model of Fama and French (FF3M, 1993) further underscores the impressive performance of the single long-term macroeconomic growth factor. We consider two versions of the FF3M. One where we leave the constant and the risk prices unrestricted, and one where we impose the no-arbitrage restrictions of a zero intercept and risk prices that are equal to the sample average return of the factors. First, the model with low frequency macroeconomic risk obtains an R^2 that is almost identical to the unrestricted version of the FF3M, even though this model contains two additional factors. The MAPE is slightly smaller for the FF3M, but the difference is never larger than 20 basis points. Importantly, the unrestricted FF3M obtains this fit with the intercept and both MKT and HML risk premia varying wildly across the three sets of test assets. In contrast, the price of macroeconomic risk at scale $j > 4$ is stable across portfolios and the intercept is always insignificant. The performance of the long-term macro risk model is even more impressive when compared to the restricted version of the FF3M.

In all, the evidence so far on the pricing of macroeconomic growth risk suggests that investors are particularly concerned about low frequency fluctuations in growth, and discount stock and bond prices for exposure to this risk.

3.3 Simulation

In this section, we conduct a simulation experiment to determine the likelihood that our evidence is spurious in the spirit of Chan et al. (1998), Kan and Zhang (1999), and Lewellen et al. (2010). One could argue that our method will succeed in picking stocks that behave alike for many possible reasons, just because their last five years of returns were similar. As a result of that, the stocks may also co-move similarly with our macroeconomic factor, independent of whether this factor is truly priced. This concern is exacerbated by the small-sample issues surrounding the estimation of our low frequency betas.

To address this concern, we construct pseudo-samples of an artificial macroeconomic growth series and analyze the size of our test. We ask how often exposure to the high and low frequency components of this artificial series capture a risk premium under the null of no cross-sectional predictability. For this simulation, we use the realized returns of individual stocks and portfolios. We find that this choice is conservative relative to returns simulated from a CAPM as in Ang et al. (2011).[23] This finding is consistent with Kan and Zhang (1999), who argue that since realized

[23] These results are available upon request.

returns are non-normal, conditionally heteroskedastic, and serially (cross-) correlated, the t-tests are biased. As a result one is more likely to reject the null of no cross-sectional predictability in each simulation, thus reducing the significance of our estimates in the data.

To start, we simulate $B = 500$ pseudo-samples of an artificial macroeconomic growth series, denoted IPG^b_{t+1}, according to the $AR(1)$-process

$$IPG^b_{t+1} \;=\; \psi + \phi IPG^b_t + \varepsilon^b_{IPG,t+1}. \tag{12}$$

The artificial series are modeled after the true IPG series, for which we estimate the $AR(1)$ in-sample. In particular, we fix the intercept ψ and the autoregressive coefficient ϕ at their sample values, whereas $\varepsilon^b_{IPG,t+1}$ is a simulated normally distributed zero mean error with variance also fixed at its sample value. Then, the initial realization IPG^b_1 in each pseudo-sample is sampled from a normal distribution with mean and variance equal to the unconditional mean and variance of IPG.

We next run the component-wise cross-sectional asset pricing tests for each artificial macroeconomic growth series, focusing on the joint model that includes both the high and low frequency component of macroeconomic risk: $j = 1:4$ and $j > 4$. First, we estimate scale-wise exposures for all individual stocks in the CRSP file over a rolling five-year window as in Section 3.1, denoted $\varphi^{b,(j)}_{i,t}$. These first-stage betas are then used as independent variables in the cross-sectional regression

$$R^e_{i,t+1} = \lambda^b_{0,t} + \lambda^{b,(1:4)}_t \varphi^{b,(1:4)}_{i,t} + \lambda^{b,(>4)}_t \varphi^{b,(>4)}_{i,t} + \alpha^b_{i,t+1}, \tag{13}$$

in each quarter t+1. The simulated macroeconomic prices of risk of interest are the time-series averages of the coefficients $\lambda^{b,(1:4)}_t$ and $\lambda^{b,(>4)}_t$. Second, we estimate the portfolio-level cross-sectional regressions of Section 3.2:

$$E[R^{e,i}_{t+1}] = \lambda^b_0 + \lambda^{b,(1:4)} \varphi^{b,(1:4)}_p + \lambda^{b(>4)} \varphi^{b,(>4)}_p + a^b_i, \tag{14}$$

where the exposures, $\varphi^{b,(j)}_p$, are estimated over the full pseudo-sample.

Table 6 presents the results of this simulation. Panel A reports the percentiles of the distribution of simulated prices of risk in each of the four cross sections under consideration (individual stocks and three sets of portfolios). In Panel B, we present two-sided rejection rates at the 5%-level, where the simulated t-statistics are based on Fama and MacBeth (1973) standard errors at the stock-level and GMM standard errors at the portfolio-level.

[Insert Table 6 about here.]

Three results stand out. First, both the simulated prices of high and low frequency risk are centered around zero in each cross section, consistent with the fact that the factors are artificial. Second, Panel B demonstrates that the individual stock-based test does not over-reject dramatically. The null hypotheses $H_0 : \lambda^{b(1:4)} = 0$ and $H_0 : \lambda^{b(>4)} = 0$ are rejected in 5.2% and 10.6% of the pseudo-samples, respectively. Furthermore, the 99th percentile of the simulated distribution of $\lambda^{b(>4)}$ among individual stocks, 1.97%, is below the estimate of 2.10% in the data. Thus, our low frequency macroeconomic risk premium is unlikely to be spurious.

Third, we see that the distribution of simulated risk-prices is much wider among portfolios. Consequently, the test over-rejects dramatically with rejection rates over 38%. This finding is consistent with the size-problems in portfolio-level tests documented in Kan and Zhang (1999) and Lewellen et al. (2010), and suggests that individual stocks may provide an attractive alternative cross section for testing asset pricing models consistent with arguments in Ang et al. (2011). Note, however, that the rejection rates are similarly large for high and low frequency risk, which suggests that the two frequencies are not so different in terms of signal-to-noise ratio. Indeed, irrespective of the wider confidence intervals, each individual portfolio-level estimate of the price of low frequency macroeconomic risk is also quite unlikely to be spurious. For the three sets of 25, 11, and 30 portfolios, respectively, our estimate in the data falls outside the 95th, 80th, and 95th percentile of the simulated distribution. In contrast, both the insignificant point estimates in the data and their position around the center of the simulated distribution suggest that high frequency risk is not priced at the portfolio-level.

To firmly conclude our argument in favor of priced low frequency macroeconomic risk, we present joint rejection rates at the bottom of Panel B. We ask how often we see a price of risk that is (i) consistent in sign and (ii) significant in each of the four cross sections. The short answer: almost never. In only 2.4% of the simulated samples we consistently reject the null that $\lambda^{b(>4)}$ is zero. Thus, we conclude that our low frequency macroeconomic growth risk is not a spurious factor.

3.4 Comparison with long-run risk betas

The previous sections provide strong evidence in favor of a single source of macroeconomic growth risk in the cross-section of asset returns. Our measure of risk captures the co-movement between the component of returns with half-life larger than four years with innovations in the component of macroeconomic growth risk with identical half-life. The focus on exposure in a long-run component of returns separates our work from the long-run risk model of Bansal and Yaron (2004), which instead measures exposure to long-run macroeconomic growth risk in short-term, single period returns.

In the following, we run a "horse race" between our measure of long-term risk and a standard measure of long-run risk commonly used in the literature inspired by Bansal and Yaron (2004). In particular, Hansen et al. (2008) show that the unconditional expected excess log return on asset i, $r_{t+1}^{e,i} = r_{t+1}^{i} - r_{t+1}^{f}$, can be written as

$$E\left[r_{t+1}^{e,i}\right] + \frac{1}{2}V(r_{t+1}^{i}) \simeq (\gamma - 1)\, cov\left(r_{t+1}^{e,i}, (E_{t+1} - E_t)\sum_{s=0}^{\infty}\beta^s\left(c_{t+1+s} - c_{t+s}\right)\right)$$

by log-linearization of the Euler condition with recursive preferences and with an intertemporal elasticity of substitution equal to one. The covariance term on the right-hand side can be further broken down into an unconditional covariance term, and a covariance between the conditional expectation of discounted consumption growth rates and the conditional expectation of the excess asset return. Estimating the conditional moments of consumption would require the use of a VAR model to capture consumption dynamics, thus introducing additional and substantial estimation error. To sidestep this problem, we follow Malloy et al. (2009) and estimate the right-hand side of the above equation using only the unconditional covariance term, $cov\left(r_{t+1}^{e,i}, \sum_{s=0}^{16}\beta^s\left(c_{t+1+s} - c_{t+s}\right)\right)$. Here we have truncated the infinite sum to an horizon of $S = 16$ quarters as in their preferred specification. This measure of long-run risk is also close to the ultimate consumption model of Parker and Julliard (2005).

To empirically compare the two competing measures of long-run risk, we run the following cross-sectional regressions for each of the three sets of portfolios under consideration:

$$E\left[r_{t+1}^{e,i}\right] + \frac{1}{2}V(r_{t+1}^{i}) = \lambda_0 + \lambda^{(>4)}\ \beta_i^{(>4)} + \lambda_{LRR}\ \beta_{i,LRR} + \alpha_i\ , \tag{15}$$

where $\beta_i^{(>4)}$ and $\beta_{i,LRR}$ are estimated from two separate univariate regressions:

$$R_{t+1}^{e,i,(>4)} = c_i^{(>4)} + \beta_i^{(>4)} u_{CG,t+1}^{(>4)} + \varepsilon_{i,t+1}^{(>4)}, \text{ and} \tag{16}$$

$$r_{t+1}^{e,i} = c_i + \beta_{i,LRR} \left(\sum_{s=0}^{16} \beta^s \left(c_{t+1+s} - c_{t+s} \right) \right) + \varepsilon_{i,t+1}. \tag{17}$$

To ensure that this comparison is purely based on how risk is measured, we now estimate the scale-wise exposure $\beta_i^{(>4)}$ to innovations at scale $j > 4$ in consumption growth (CG), instead of industrial production growth (IPG).[24]

Table 7 reports the results for this two-factor model as well as for separate single factor models. In all cases, standard errors are calculated using the GMM approach described in Section 3.2.2. In the single factor model with $\beta_{i,LRR}$, we find a positive price of long-run risk, $\lambda_{i,LRR}$, that is marginally significant in two out of three sets of portfolios. In the joint model, however, $\lambda_{i,LRR}$ turns small and insignificant in each case, whereas the scale-wise price of low frequency risk, $\lambda^{(>4)}$, is consistently large and significant.[25] Indeed, since the cross-sectional R^2 does not increase when $\beta_{i,LRR}$ is added, we conclude that our horizon-specific measure of low frequency risk captures fundamental macroeconomic risk as it is perceived by investors more adequately than betas estimated from high frequency stock returns. This tight link between exposures in long-term returns to long-term growth risk suggest that the (buy-and-hold) horizon of the marginal investors is long, approximately four years. This finding is consistent with Cohen et al. (2009), who argue that many important investment decisions of corporate managers, pension and endowment funds, and individuals have such long horizons.

[Insert Table 7 about here.]

In Table IA.1 of the Internet Appendix, we present results for three additional risk measures, each combining separate elements from our scale-specific consumption growth risk measure ($\beta^{(>4)}$) and from the long-run risk measure (β^{LRR}). As a benchmark, we first estimate a standard consumption-CAPM (β_{CCAPM}), where risk is measured with a regression of *one quarter excess returns* on *one*

[24]The results for IPG are almost identical and available upon request. See also Panel A of Table IA.6, which presents the portfolio-level tests of Section 3.2 for scale-wise exposures to CG.

[25]Note, whenever $\beta_{i,LRR}$ is used, the left hand side in the cross-sectional regression is the average log excess return of the portfolios. In contrast, in the model with $\beta_i^{(>4)}$ alone, the left-hand side is the average simple excess return. This choice ensures consistency with previous work and is inconsequential for the results.

quarter consumption growth. Second, we estimate a four-year consumption-CAPM (β^{4YR}_{CCAPM}), where risk is measured by regressing the left-hand side from our scale-specific risk measure (*four-year excess returns*) on the right-hand side from the long-run risk measure (*four-year consumption growth*). The third model measures risk with a regression of the left-hand side from the long-run risk model (current *one quarter excess log returns*) on the right-hand side from our scale-specific risk model (*the innovation in future four-year consumption growth*. We dub this model hybrid and denote its implied risk measure β_{hybrid}). Among these three alternative measures it is only β^{4Y}_{CCAPM} that captures a (marginally) significant price of risk in each set of portfolios. The cross-sectional fit is considerably worse than in the case of our scale-specific risk measure, however, such that it is no surprise that β^{4Y}_{CCAPM} is driven out in a horse race. We conclude that the superior performance of our scale-specific risk measure derives from both using long-term returns, rather than short-term returns, and measuring risk as an innovation in long-term growth, rather than its level.

4 Macroeconomic growth and volatility risk

The asset pricing implications of macroeconomic volatility risk receive considerable attention in recent literature. For instance, in the long-run risk model of Bansal and Yaron (2004), a rise in consumption volatility increases risk premiums on all assets (and thus lowers valuations contemporaneously), because agents dislike economic uncertainty (see, also, Bansal, Khatchatrian, Yaron (2005)). Moreover, in the cross section, an asset that provides high returns when volatility increases, should have low expected returns, because this asset is attractive as a hedge. A similar prediction follows from the Intertemporal-CAPM with stochastic volatility studied in Campbell et al. (2014).

Empirically, point estimates of the market price of volatility risk are negative consistent with this prediction. However, the cross section of exposures underlying these point estimates is a topic of heated debate. On one hand, Campbell et al. (2014) find that volatility risk exposures explain a considerable amount of cross-sectional variation in the average returns of a wide variety of test assets, including stocks, bonds, and currencies. The estimated volatility beta for stocks is generally positive in their case, however. This finding is quite hard to justify (i) from the perspective of economic models that predict a positive correlation between innovations in market volatility and risk premiums when agents prefer early resolution of uncertainty, and (ii) given empirical evidence of high market volatility and concurrent stock market declines (e.g., during the recession of 2008).

On the other hand, Bansal et al. (2014) obtain estimates of volatility exposures that are generally negative for stocks. But in their case volatility risk explains only a modest fraction of the cross-sectional variation in average returns for a small set of stock portfolios.[26]

In this paper, we analyze whether decomposing macroeconomic volatility risk across horizons can bridge the gap between the empirical evidence in these two papers. Following the setup of our tests for growth, we first estimate scale-wise prices of risk for macroeconomic volatility in the cross section of individual stocks. Next, we analyze pricing at the portfolio-level. Finally, we investigate whether horizon-dependent volatility risk represent a source of risk that is separate from growth. Section 5 contains a range of robustness checks for these tests.

4.1 Individual stock-level tests

At the end of each quarter t, we run cross-sectional regressions of individual stock returns on exposures to scale-wise volatility innovations, $u^{(j)}_{IPVOL,t}$, where IPVOL is the AR(1)-GARCH(1,1) conditional volatility of IPG. These regressions are analogous to Eqs. (7) and (8) with $u^{(j)}_{IPG,t}$ replaced by $u^{(j)}_{IPVOL,t}$.[27]

We present the results for these regressions in Panel A of Table 8. We observe small and insignificant prices of high frequency volatility risk ($j = 1 : 4$), but an economically large and significant price of low frequency volatility risk ($j > 4$) at -1.58% in a single factor model, and -2.07% in the two-factor model that controls for high frequency volatility risk.[28] The fact that exposure to macroeconomic volatility risk predicts individual stock returns with a negative sign is consistent with the long-run risk framework and the intuition that stocks which comove with (long-term) volatility are attractive as a hedge and thus have high prices. The last three rows of Panel A show that this conclusion is robust to the inclusion of characteristics (size and book-to-market) as well as short- and long-term exposures to benchmark traded factors (MKT, SMB, and HML).

[26]Note that Campbell et al. (2014) analyze the volatility of stock market returns directly, whereas Bansal et al. (2014) analyze consumption (or cash-flow) volatility. The reason is that the variance of returns is a scaled version of the variance of consumption in the long-run risk framework (see Eq. (A13) in Bansal and Yaron (2004)). If return variance is driven by discount-rate variation in the data, however, return variance may not be easily connected to cash-flow volatility. We acknowledge that this distinction may therefore be important, but focus on a pure macroeconomic measure of volatility risk consistent with our analysis of growth risk.

[27]As in the case of growth, the volatility innovations $u^{(j)}_{IPVOL,t}$ are measured as the first-difference in the components of IPVOL.

[28]When we include all high frequency components separately, the price of low frequency volatility risk increases even further to -2.79%.

[Insert Table 8 about here.]

In Panel B of Table 8 we perform an out-of-sample test for the pricing of volatility (see the discussion in Section 2.3). For Panel A, IPVOL is estimated using the full sample of data and therefore subject to a look-ahead bias. To construct a real-time measure of conditional volatility in quarter t (denoted IPVOL-OOS), we estimate the AR(1)-GARCH(1,1) process over an expanding window that uses only historical IPG observations. We then extract the components of IPVOL-OOS, and use their innovations, $u^{(j)}_{IPVOL-OOS,t}$, to compute volatility exposures. The evidence from this out-of-sample exercise is by and large similar to the case of IPVOL: low frequency volatility risk captures a large and significant price relative to high frequency volatility risk.

4.2 Portfolio-level tests

Analogous to Section 3.2 we now run asset pricing tests for three sets of portfolios (25 size and book-to-market portfolios, 11 stock and bond portfolios, and 30 portfolios sorted on various characteristics). Table 9 presents scale-wise volatility risk exposures (denoted $\delta_i^{(j)}$). Table 10 presents scale-wise prices of risk (denoted $\lambda_{vol}^{(j)}$). For the sake of brevity, we discuss the pricing evidence first.

[Insert Table 9 and 10 about here.]

Panel A of Table 10 shows that exposure to low frequency IPG volatility risk captures a large and significant negative price of risk of about -2% in each cross-section. In contrast, the price of high frequency IPG volatility risk is insignificant and positive, which sign is counterintuitive. Needless of a large intercept, the single, low frequency, macroeconomic volatility risk factor provides an adequate cross-sectional fit, with R^2's and MAPE's that are only slightly worse than the single macro-growth factor as well as the Fama and French (1993) three-factor model (see Table 5).

Table 9 demonstrates that the negative price of low frequency risk and adequate cross-sectional fit follow from exposures to low frequency volatility risk that are (i) negative for all portfolios considered (that is, prices of all portfolios tend to fall when long-run volatility is increasing) and (ii) typically more negative for those assets with larger average returns (for example, small versus big, value versus growth, long versus short maturity bonds, stocks versus bonds, and low versus high short-term returns and investment).[29]

[29] In unreported results, we find that the straddle position of Coval and Shumway (2001) has a positive and large volatility risk exposure at both the low and high frequency, which finding confirms the intuition that a straddle hedges volatility risk. We thank the authors for sharing the straddle return series.

Thus, we find that when we measure volatility risk exposures over long horizons, macroeconomic volatility matters in the manner suggested by theory. This finding reconciles inconsistent evidence in recent literature. On one hand, we confirm the premise of Bansal et al. (2014) that equities carry positive macroeconomic volatility risk premia ($\delta_{i,t}^{(>4)} \times \lambda^{vol(>4)} > 0$), which contrasts negative risk premia found in Campbell et al. (2014). On the other hand, we confirm Campbell et al. (2014) by showing that volatility risk explains a large fraction of cross-sectional variation in average asset returns. In this dimension, our findings contrast Bansal et al. (2014), who focus on a small cross section of ten size and book-to-market sorted portfolios and find that not-decomposed volatility risk explains about 10% to 50% of these assets average returns. This fraction is modest compared to R^2's of $61\%, 88\%$ and 52% in Panels A, B and C of Table 10, respectively. Moreover, Bansal et al. (2014) estimate a positive volatility beta for value-minus-growth. In contrast, this paper and Campbell et al. (2014) estimate a negative volatility beta for value-minus-growth, which is more consistent with both theoretical models of real options held by growth firms (see, e.g., McQuade (2012)), and stylized facts (for example, how value-minus-growth bets performed during the Great Depression, the Tech Boom, and the Great Recession).

4.3 Growth versus volatility risk

The previous sections provide evidence that both long-term components of growth and volatility predict returns in the cross-section. This finding begs the question whether these two sources of risk capture common long-term macroeconomic fluctuations or whether volatility contains orthogonal information to growth. To answer this question, we estimate the following two-factor model at the stock- and portfolio-level, respectively:

$$R_{t+1}^{e,i} = \lambda_{0,t} + \lambda_{growth,t}^{(>4)} \ \beta_{i,IPG,t}^{(>4)} + \lambda_{vol,t}^{(>4)} \ \beta_{i,IPVOL,t}^{(>4)} + \alpha_{i,t} \ , \tag{18}$$

$$E[R_{t+1}^{e,i}] = \lambda_0 + \lambda_{growth}^{(>4)} \ \beta_{i,IPG}^{(>4)} + \lambda_{vol}^{(>4)} \ \beta_{i,IPVOL}^{(>4)} + \alpha_i \ , \tag{19}$$

where $\beta_{i,IPG}^{(>4)}$ and $\beta_{i,IPVOL}^{(>4)}$ denote scale-wise risk loadings of asset i with respect to innovations in long-term growth and long-term volatility, respectively. At the stock-level, we let these exposures vary over time. The market prices of risk of interest are the time-series average of the $\lambda_t^{(>4)}$'s at the stock-level and the estimated $\lambda^{(>4)}$'s at the portfolio-level. In both cases, the scale-wise exposures $\beta_{i,IPG}^{(>4)}$ and $\beta_{i,IPVOL}^{(>4)}$ are obtained from two separate, simple regressions. This approach is desirable for two reasons. First, the component of returns at scale $j > 4$ is persistent, and this persistence may give rise to additional small sample biases when estimating the two betas jointly. Moreover, as argued in Kan et al. (2013), using separate, simple regressions ensures that, when the estimated price of volatility risk is significant, one can conclude that volatility contributes to explaining cross-sectional variation in returns after controlling for growth. One cannot draw this conclusion in the case of multiple regression betas, because growth betas also change when volatility is added, unless the two risk factors are uncorrelated.[30] Table 11 presents the results.

[Insert Table 11 about here.]

Compared to what we have seen before, the estimated prices of risk for growth and volatility are consistent in sign, but smaller economically and statistically. Using individual stocks, the estimated price of growth risk is 1.57%, with a marginally significant t-statistic of 1.96. The estimated price of volatility risk is -1.29%, with an insignificant t-statistic of -1.42. At the portfolio-level, the price of growth risk ranges from 1.18% to 1.67% and is significant for 25 size and book-to-market portfolios and 30 portfolios sorted on various characteristics. On the other hand, the price of volatility risk hovers around -1%, but is significant only for the larger set of 30 portfolios. Consistent with this evidence, we see that adding volatility does not meaningfully improve the cross-sectional fit relative to a model with a single growth factor, except possibly for the larger set of 30 portfolios.[31] In all, we conclude that fluctuations in long-term growth and volatility largely capture common long-term macro-risk that is a key determinant of cross-sectional expected return variation. The fact that volatility risk is significant in the case of 30 portfolio sorted on various characteristics suggests, however, that long-term fluctuations in volatility may contain a small and hard-to-identify orthogonal component of risk.

5 Robustness checks

In this section we describe a range of robustness checks for which results are presented in the Internet Appendix.

[30] Naturally, it is also instructive to compare the cross-sectional fit (R^2 and MAPE) when volatility is added to growth.

[31] From Table 5, the R^2's are 69%, 91%, and 64%, respectively, for the model with growth, whereas we obtain 72%, 92%, and 71%, respectively, for the joint model.

5.1 Alternative specifications of the stock-level cross-sectional regression

Table IA.2 demonstrates that the conclusions drawn from the stock-level cross-sectional regressions of Table 2 are robust to changing the length of the rolling window to six (Panel A) and ten years (Panel B) as well as when updating the betas only once a year at the end of December (Panel C). Second, Table IA.3 uses monthly IPG data to examine the robustness of our results to changes in the frequency of observation. To be precise, for monthly IPG, we separate high and low frequency risk at scales $j = 1 : 5$ versus $j > 5$. Thus, we capture shocks with a half-life below or above $2^5 = 32$ months, or about 2.7 years. In short, the price per cross-sectional standard deviation in exposure to long-term risk (i.e., $j > 5$) is large at about 2%, significant, and not captured by the usual control variables (Panel B). On the contrary, the price of risk for short-term fluctuations ($j = 1 : 5$) is below 1% and insignificant. These findings suggest that the horizon over which macroeconomic risk matters most is likely starting somewhere slightly below four years. Moreover, this robustness check is important, because the (re-) investment horizon of investors is unknown. Our evidence suggests that investors care most about low frequency risk when choosing their portfolio and this conclusion is independent of the frequency at which investors update their portfolio (see, also, Kamara et al. (2014)).

[Insert Tables IA.2 and IA.3 about here.]

5.2 Alternative measures of macroeconomic growth

Our conclusions are robust to alternative measures of macroeconomic growth: consumption growth (CG) and a composite measure of real activity based on industrial production, consumption, employment, and unemployment in the spirit of Ang and Piazzesi (2003) (CRAG).[32] The former alternative is particularly interesting given that the Consumption-Based Asset Pricing Model (CBAPM) of Lucas (1978) and Breeden (1979) lies at the heart of modern asset pricing. The CBAPM predicts that the covariance with contemporaneous consumption growth explains all cross-sectional variation in asset returns. Historically, this prediction has received little support in the data. A possible explanation for this failure is put forward in, e.g., Breeden et al. (1989) and Savov (2011): mismeasurement in consumption data. Therefore, Malloy et al. (2009) and Savov (2011) propose to use alternative measures of consumption that are more volatile and more correlated with stock

[32]See the data description in Appendix A.

returns, that is, stockholder consumption and garbage, respectively. Recently, Kroencke (2014) suggests that suitably unfiltering of consumption performs well when pricing a small set of stock portfolios. In contrast to these authors, and in line with Bandi and Tamoni (2014), we use the standard consumption measure and show that only low frequency components of this original series matter for asset pricing. In fact, we find that these low frequency components matter more than unfiltering in a horse race.

Table IA.4 presents stock-level cross-sectional regressions similar to Table 2. In Panel A we estimate lagged scale-wise exposures to innovations in the components of CG. We see similar patterns as before. Exposure to low frequency fluctuations at scale $j > 4$ is a robust predictor of individual stock returns, with a price of risk that is (i) large and significant ranging from about 1.3% to 1.8% per cross-sectional standard deviation in exposure and (ii) robust to the inclusion of characteristics and short- and long-term exposures to MKT, SMB, and HML. In contrast, the price of high frequency risk is small and insignificant. Thus, once consumption is suitably decomposed across scales, exposure to its long-term fluctuations plays a key role in explaining cross-sectional variation in stock returns as predicted by the CBAPM. We argue that this conclusion is general for measures of macroeconomic growth. Indeed, Panel B of Table IA.4 shows qualitatively similar, but quantitatively stronger results for CRAG.

Table IA.5 forms quintile portfolios based on exposures to innovations in the components of CG (Panel A) and CRAG (Panel B), as in Table 3. In both panels, the left block of results covers the evidence for high frequency risk at scale $j = 1 : 4$, whereas the right block covers the evidence for low frequency risk at scale $j > 4$. Consistent with our previous findings, we observe that average returns increase monotonically in exposure only for $j > 4$. As a result, High-minus-Low average return spreads are large for low frequency risk at 3.26% ($t = 2.17$) for CG and 4.96% ($t = 3.43$) for CRAG, which translates to Sharpe ratios of 0.32 and 0.50, respectively. For these alternative measures, the post-ranking exposure of the High-minus-Low spreading portfolio is also significant at $j > 4$.

Table IA.6 shows the results from portfolio-level cross-sectional regressions for the alternative measures of growth. In all cases, the price of low frequency macroeconomic risk is large and significant at about 2% in a single factor model, whereas it drives out high frequency risk in a joint model. In case of both CG and CRAG, a single low frequency macroeconomic risk factor obtains an adequate cross-sectional fit, without violating the zero-intercept restriction. Again, we note that the fit of this single-factor model is on par with the three-factor model of Fama and French (1993).

[Insert Tables IA.4, IA.5 and IA.6 about here.]

Table IA.7 runs a horse race of our measure of consumption risk versus the unfiltered consumption measure of Kroencke (2014).[33] In short, we see that the cross-sectional fit provided by a single unfiltered consumption factor is considerably worse among 25 and 30 portfolios. Furthermore, in each of the three cross-sections, the unfiltered consumption factor is insignificant when included next to our low frequency consumption risk. The dominance of low frequency consumption risk suggests that zooming in on a long-term component of consumption achieves more than just filtering out measurement error in quarterly NIPA consumption.

[Insert Table IA.7 about here.]

5.3 Bryzgalova (2015) penalized cross-sectional regression

Table IA.8 asks whether our estimate for the price of low frequency IPG risk is robust to the penalized cross-sectional regression procedure of Bryzgalova (2015), denoted Pen-FM. Pen-FM penalizes the risk-prices of weak factors. Intuitively, factors are called "weak" when they have low correlation with (components of) returns in the time-series. In short, within our setting the Pen-FM procedure does not meaningfully shrink the risk-price at $j > 4$ in any set of portfolio, so that the estimated price of low frequency growth risk is in fact close to the standard Fama and MacBeth (1973) estimates displayed in Table 5. In contrast, the Pen-FM approach shrinks the price of high frequency growth risk by a large amount, amounting to a zero risk-price in two out of three sets of portfolios. Following Bryzgalova (2015), we also perform a bootstrap experiment to evaluate the significance of these estimates.[34] Two results stand out from the bootstrap. First, the Pen-FM estimates are significant using bootstrapped standard errors for the long-term component at scale $j > 4$. Second, the number of bootstrap simulations with non-positive risk-price estimates is quite small at below 10% for $j > 4$, relative to over 52% for $j = 1 : 4$. In all, these findings show that low frequency

[33] Our risk measure is exposure to low frequency variation at scale $j > 4$ in standard NIPA, per capita, non-durables and services consumption growth as in Table IA.6. For exposure to unfiltered consumption, we use the annual series that works best empirically in Kroencke (2014), i.e, quarter four to quarter four non-durables (ex. services) consumption growth adjusted for the effects of time aggregation and filtering. We thank the author for sharing this data.

[34] Additional details for the bootstrap are available upon request from the authors.

growth risk is not a weak factor and, thus, our conclusion that low frequency growth risk is strongly priced in the cross-section (relative to high frequency growth risk) is unlikely spurious.

[Insert Table IA.8 about here.]

5.4 Robustness checks for volatility

Table IA.9 and Table IA.10 provide the same robustness checks at the stock- and portfolio-level for the case of volatility risk. In short, we see that low frequency variation in macroeconomic uncertainty, denoted CVOL in case of consumption and CRAVOL in case of the composite measure, is a key determinant of returns in the cross-section.

[Insert Tables IA.9 and IA.10 about here.]

For each of these alternative measures, Table IA.11 further investigates whether there is independent variation in volatility risk that is priced on top of growth risk (in a manner analogous to Table 11). For the composite measure, we see that the price of CRAVOL risk is large at the stock-level. Similar to the case of IPG, however, CRAG risk dominates at the portfolio-level.[35] Consequently, the cross-sectional explanatory power of the joint model is similar to the model with CRAG alone (see Table IA.5). For the case of consumption, we see that the price of CVOL risk is large and (marginally) significant in each cross-section, whereas the price of CG risk is small in magnitude and significance relative to the model with CG alone.[36] Perhaps unsurprisingly, then, the joint model presents a meaningful improvement in cross-sectional fit over the model with CG alone, with an increase in R^2 of about 10% in each set of portfolios. Note, however, that the improvement in cross-sectional fit is much less impressive when compared to the model with CVOL alone (see Table IA.10).

[Insert Table IA.11 about here.]

In all, the evidence is again consistent with a large common component of long-term macro-risk in growth and volatility. In most specifications using either industrial production, consumption, or the composite measure of real activity, a joint model with growth and volatility does not provide

[35] The price of CRAG risk is 2.42% (stock-level), 2.30% (25 portfolios), 2.70% (11 portfolios) and 1.75% (30 portfolios) in Tables IA.4 and IA.5, and is 0.13%, 1.36%, 2.24%, and 1.59%, respectively, when CRAVOL risk is added.

[36] The price of CG risk is 1.81% (stock-level), 2.04% (25 portfolios), 2.54% (11 portfolios) and 1.68% (30 portfolios) in Tables IA.4 and IA.5, but falls to 0.34%, 0.55%, 1.33% and 0.88%, respectively, when CVOL risk is added.

a sizeable improvement in cross-sectional fit over a single factor model with growth (or volatility). There are a number of specifications where volatility is significant in the presence of growth, however, thus suggesting that long-term volatility risk may contain some, though hard-to-identify, orthogonal information about returns.

6 Conclusion

We test whether macroeconomic risk is an important determinant of asset returns, and more particularly at which horizon this connection is strongest. If macroeconomic growth and volatility are driven by shocks with heterogeneous degrees of persistence, then risk premia will reflect the collection of compensations for exposure to these heterogeneous shocks. Thus, to uncover the link between risk premia and the real economy, it is key to account for this persistence heterogeneity.

We show that long-term risk, measured as the covariance between four-year returns with innovations in economic growth and volatility with matching half-life, is priced. This four-year horizon follows directly from our decomposition. In contrast, shorter-term risk is not priced. Quantitatively, a simple regression in the cross section of individual stocks shows that a standard deviation increase in a stock's historical exposure to long-run macroeconomic growth risk captures a positive risk premium of 2.50% annually. Conversely, a standard deviation increase in a stock's exposure to long-run macroeconomic volatility risk captures a negative risk premium of -1.6% annually. These economically large and significant premia for exposure to long-term macroeconomic risk are robust to the inclusion of stock characteristics and benchmark traded factors, and they are also present in the cross-section of average returns of stock and bond portfolios. Remarkably, a single, long-term macro-risk factor provides an adequate cross-sectional fit that is comparable to the three-factor model of Fama and French (1993).

Our evidence highlights the importance of measuring risk as exposure in long-term returns to long-term risk. This approach is different from the framework of Bansal and Yaron (2004), where risk is measured as exposure in single period returns. We find that such measures of long-term risk do predict average portfolio returns in isolation, but are driven out by our scale-wise four-year risk measure in a horse race. This dominance of risks measured in long-term returns suggests that the horizon of the marginal investor is long. Therefore, we conjecture that models that feature investors with heterogeneous (and possibly stochastic) horizons may prove particularly useful to understand the link between asset prices and the macroeconomy.

Furthermore, our results for volatility represent an important contribution to recent literature. On one hand, we confirm the premise of Bansal et al. (2014) that equities carry positive (macro-) volatility risk premia, which contrasts Campbell et al. (2014). On the other hand, we confirm the finding in Campbell et al. (2014) that low frequency variation in volatility explains a large fraction of cross-sectional variation in average asset returns, which, in turn, contrasts Bansal et al. (2014). Both findings are in line with macro-finance theory and intuition. That said, our results do suggest that long-term fluctuations in growth and volatility capture largely common risk.

In summary, we show that it is crucially important to account for horizon-specific exposures to macroeconomic risk when connecting prices in financial markets to the real economy. Indeed, our evidence resuscitates a central role for business and medium-term cycle (see Comin and Gertler (2006)) aggregate risk as a key determinant of equilibrium asset prices. Theoretical models should generate scale-wise risk-return patterns in equilibrium that are consistent with this evidence.

A Data

- Industrial production: We use the (latest vintage) seasonally-adjusted Industrial Production Index of the $FRED^{®}$ database of the St. Louis FED. This series is designed to gauge real output and overall economic activity in the US. Quarterly growth rates are calculated by compounding monthly growth rates. Following previous literature (Chen et al. (1986) and Liu and Zhang (2008)), we lead the monthly industrial production series by one month, such that the timing of this flow variable is aligned with financial variables. Results are quantitatively and qualitatively robust when we do not lead the series.[37]

- Consumption: Following Jagannathan and Wang (2007), we use quarterly seasonally-adjusted aggregate nominal consumption expenditure on nondurables and services from the National Income and Product Accounts (NIPA) Table 2.3.5. We obtain population numbers from NIPA Table 2.1 and price deflator series from NIPA Table 2.3.4 to construct the time series of per capita real consumption figures.

- Employment and Unemployment: Employment is seasonally-adjusted Total Nonfarm Payroll Employment (PAYEMS) from the Current Employment Statistics in the Establishment Survey of the Bureau of Labor Statistics. Employment measures the number of U.S. workers in the economy that excludes proprietors, private household employees, unpaid volunteers, farm employees, and the unincorporated self-employed. This measure accounts for approximately 80 percent of the workers who contribute to Gross Domestic Product. Unemployment (UNEMPLOY) is seasonally adjusted and comes from the Current Population Survey in the Household Survey of the Bureau of Labor Statistics. Unemployment measures the number of persons that do not have a job, have actively looked for work in the prior 4 weeks, and are currently available for work.

- Composite measure of real activity: Similar to Ang and Piazzesi (2003), we construct a composite measure of real activity by extracting the first principal component from the correlation matrix of quarterly growth rates in industrial production, consumption, employment, and unemployment over the sample period 1948Q2 to 2011Q4. The first principal component captures 68% of the common variation in these four series.

[37] These results are available upon request.

- Returns and characteristics: Individual stock returns, market capitalizations, and book values are from the Center for Research in Security Prices (CRSP) and Compustat.[38] We include all common stocks with share codes 10 and 11, including financials, but exclude firms with negative book equity in Compustat. Returns on the various stock portfolios and benchmark factors are taken from Kenneth French's website.[39] Constant maturity treasury bond returns are from CRSP. Excess returns on these assets are calculated over the 30-day T-bill return.

[38]Book-to-Market is calculated in June of year t as the ratio of the most recently available book-value of equity in Compustat (assumed to be available six months after the $t-1$ fiscal year-end) divided by Market Capitalization at the end of year $t-1$.

[39]`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

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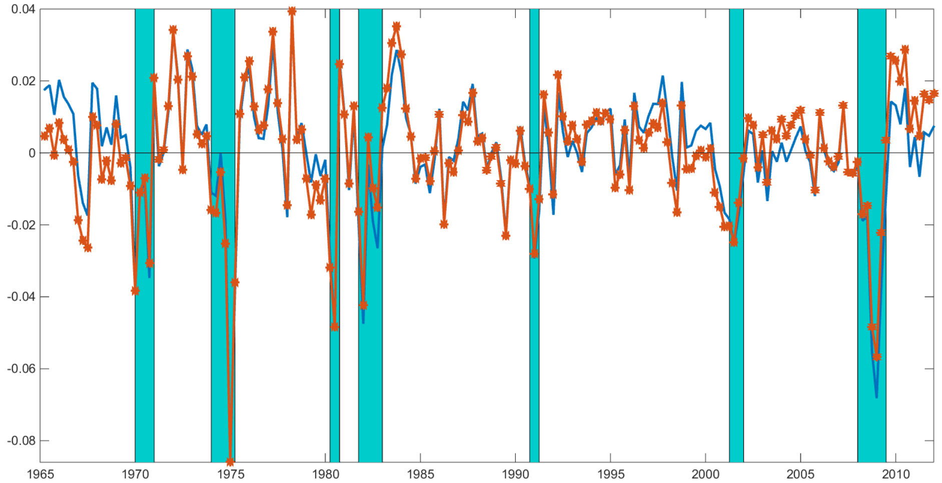
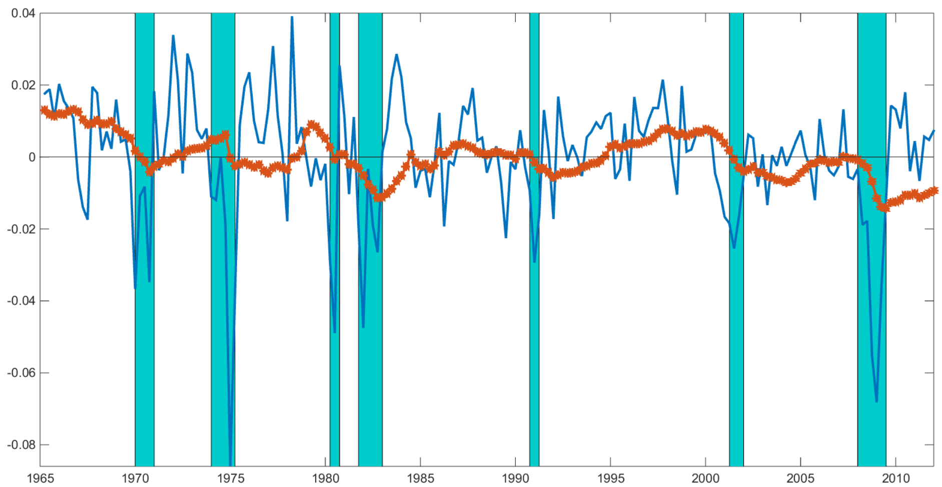
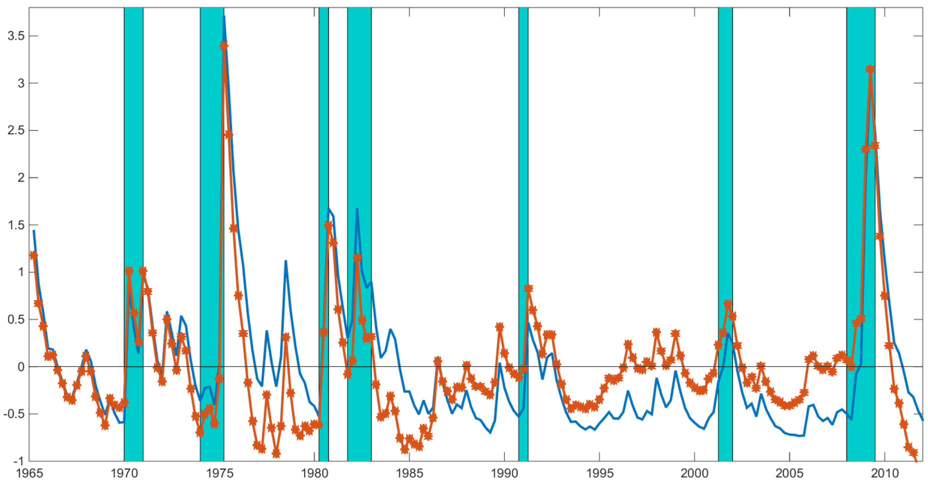


(a) IPG vs. high frequency component $IPG^{(1:4)}$.

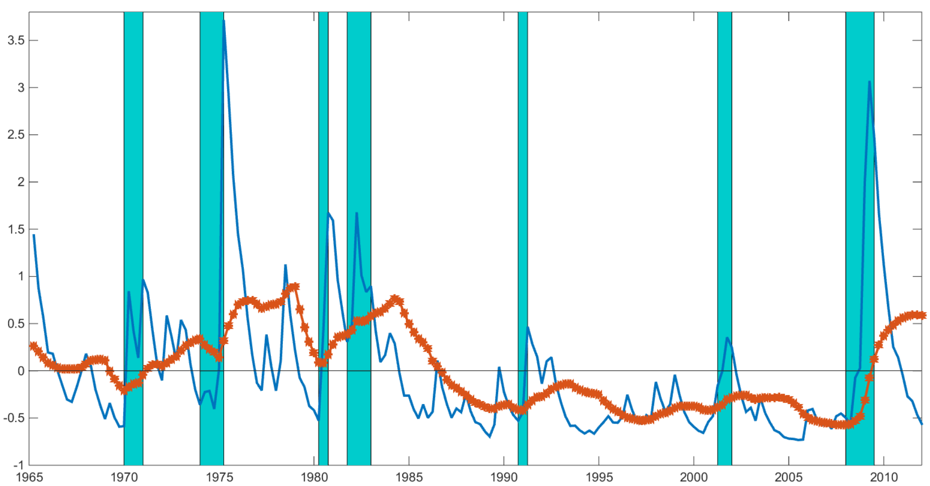


(b) IPG vs. low frequency component $IPG^{(>4)}$.

Figure 1: **Industrial production growth at different levels of persistence**
This figure plots the industrial production growth series (IPG, solid line in Panels A and B) against its high and low frequency components (solid line with stars in Panel A and B, respectively). The high frequency component is the sum of the components of IPG at scale $j = 1, ..., 4$, and captures short-term fluctuations with half-life below four years. The low frequency component is the sum of the components of IPG at scale $j > 4$, and captures long-term fluctuations with half-life above four years. The shaded areas represent NBER recessions.



(a) IPVOL vs. high frequency component $IPVOL^{(1:4)}$.



(b) IPVOL vs. low frequency component $IPVOL^{(>4)}$.

Figure 2: **Industrial production volatility at different level of persistence**.
This figure plots the conditional volatility of industrial production growth (IPVOL, solid line in Panels A and B), estimated as an AR(1)-GARCH(1,1) process, against its high and low frequency components (solid line with stars in Panel A and B, respectively). The high frequency component is the sum of the components of IPVOL at scale $j = 1, ..., 4$, and captures short-term fluctuations with half-life below four years. The low frequency component is the sum of the components of IPVOL at scale $j > 4$, and captures long-term fluctuations with half-life above four years. The shaded areas represent NBER recessions.

Table 1: **Interpretation of components across scale**
This table presents the interpretation of the scale (or persistence level) j in terms of time spans for both quarterly (Panel A) and monthly (Panel B) time series. We also present the decomposition in high and low frequency variation: $j = 1 : J$ vs. $j > J$, where the maximum scale for quarterly and monthly data, respectively, is $J = 4$ and $J = 5$.

Time-scale	Frequency resolution	Interpretation
Panel A: Quarterly calendar time		
$j = 1$	$1 - 2$ quarters	
$j = 2$	$2 - 4$ quarters	
$j = 3$	$4 - 8$ quarters	
$j = 4$	$8 - 16$ quarters	
$j = 1 : 4$	$1 - 16$ quarters	High frequency
$j > 4$	> 16 quarters	Low frequency
Panel B: Monthly calendar time		
$j = 1$	$1 - 2$ months	
$j = 2$	$2 - 4$ months	
$j = 3$	$4 - 8$ months	
$j = 4$	$8 - 16$ months	
$j = 5$	$16 - 32$ months	
$j = 1 : 5$	$1 - 32$ months	High frequency
$j > 5$	> 32 months	Low frequency

Table 2: **Macroeconomic growth risk: Cross-sectional regressions for individual stocks** This table reports second-stage cross-sectional regressions of quarterly excess stock returns on lagged estimated risk loadings. The risk loadings are first-stage component-wise betas estimated with a five-year rolling regression of the j-th component of excess returns on the innovation in the j-th component of industrial production growth ($u^{(j)}_{IPG,t}$). Panel B presents the trade-off between high and low frequency risk with controls. The first model controls for characteristics, i.e., size ($SIZE^i_t$) and book-to-market (BM^i_t), with prices denoted γ_{SIZE} and γ_{BM}, respectively. In models three and four, we control for exposure to the three factors of Fama and French (1993) estimated over a five-year rolling window of quarterly returns (as is standard in the literature) and overlapping four-year returns, respectively, denoted: β^1_X and β^{16}_X, where X=MKT,SMB,HML. We report time-series averages of the second-stage price of risk estimates (in percent per year), with Fama and MacBeth (1973) t-statistics presented underneath in parenthesis, as well as the cross-sectional R^2. The scale-wise exposures are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. The sample period is 1965.Q1 to 2011.Q4.

Panel A: The price of exposure to macro-growth risk across scales ($u^{(j)}_{IPG,t}$)

	λ_0	$\lambda^{(1)}$	$\lambda^{(2)}$	$\lambda^{(3)}$	$\lambda^{(4)}$	$\lambda^{(1:4)}$	$\lambda^{(>4)}$	R^2
$j=1$	10.04	1.07						0.008
	(3.23)	(1.91)						
$j=2$	9.67		0.80					0.008
	(3.17)		(1.44)					
$j=3$	10.17			-0.03				0.008
	(3.44)			(-0.06)				
$j=4$	9.85				0.02			0.006
	(3.27)				(0.03)			
$j=1:4$	9.78					1.25		0.009
	(3.18)					(2.08)		
$j>4$	8.98						2.50	0.011
	(2.99)						(3.67)	
$j=1:4$ & $j>4$	8.91					0.98	2.10	0.017
	(3.05)					(1.71)	(3.19)	
All	8.97	0.73	0.69	-1.23	-0.46		2.89	0.031
	(3.42)	(1.33)	(1.27)	(-1.90)	(-0.71)		(4.05)	

Panel B: Scale-wise growth risk ($j=1:4$ & $j>4$) vs. characteristics and Fama-French factors

Controls	λ_0	$\lambda^{(1:4)}$	$\lambda^{(>4)}$	γ_{SIZE}	γ_{BM}	λ^1_{MKT}	λ^1_{SMB}	λ^1_{HML}	λ^{16}_{MKT}	λ^{16}_{SMB}	λ^{16}_{HML}	R^2
$SIZE^i_t$, BM^i_t	9.52	0.26	1.82	-2.74	1.67							0.047
	(3.17)	(0.59)	(3.37)	(-2.55)	(2.60)							
β^1_{MKT}, β^1_{SMB}, β^1_{HML}	6.83	0.12	1.60			1.50	1.62	1.34				0.050
	(3.37)	(0.26)	(2.76)			(1.28)	(1.56)	(2.02)				
β^{16}_{MKT}, β^{16}_{SMB}, β^{16}_{HML}	9.30	0.97	2.60						-0.81	0.05	0.03	0.031
	(3.35)	(1.85)	(3.01)						(-2.53)	(0.20)	(0.16)	

Table 3: **Portfolios sorted on component-wise macroeconomic growth risk**
This table presents quintile portfolios sorted on exposure to either high ($j = 1:4$, columns one to four) or low ($j > 4$, columns five to eight) frequency variation in industrial production growth. We report the annualized performance (average return, standard deviation, and Sharpe ratio) and post-ranking beta of equal-weighted (Panel A) and value-weighted (Panel B) portfolios. The post-ranking beta is estimated with a component-wise regression of portfolio returns on innovations in the respective component of IPG ($u^{(1:4)}_{IPG,t}$ or $u^{(>4)}_{IPG,t}$), with t-statistic calculated using Newey and West (1987) standard errors with $2^4 = 16$ lags. Panel C presents pre-ranking beta, market share, and book-to-market ratio, which are averaged within portfolio and over time. To conserve space, we report results only for the first, third and fifth quintile as well as for the High-minus-Low spreading portfolio. The sample period is 1965:Q1 to 2011:Q4.

	High frequency risk ($u^{(1:4)}_{IPG,t}$)				Low frequency risk ($u^{(>4)}_{IPG,t}$)			
	High	Mid	Low	**High-Low**	High	Mid	Low	**High-Low**
Panel A: Equal-weighted portfolios								
Avg. Ret.	10.17	10.06	8.82	1.35	12.52	9.55	6.97	5.55
	(2.85)	(3.41)	(2.83)	(1.01)	(3.36)	(3.36)	(2.14)	(3.63)
St. Dev.	24.47	20.19	21.40	9.15	25.57	19.48	22.30	10.49
Sharpe	0.42	0.50	0.41	0.15	0.49	0.49	0.31	0.53
Post-ranking $\beta^{(j)}_{IPG,p}$	1.44	1.11	1.23	0.20	4.13	3.67	2.80	1.33
	(3.18)	(2.84)	(2.62)	(0.86)	(3.41)	(4.46)	(2.47)	(1.45)
Panel B: Value-weighted portfolios								
Avg. Ret.	9.31	9.58	7.60	1.70	11.77	8.97	6.74	5.03
	(2.65)	(3.38)	(2.51)	(1.21)	(3.20)	(3.24)	(2.14)	(3.14)
St. Dev.	24.05	19.41	20.79	9.65	25.24	19.00	21.65	10.99
Sharpe	0.39	0.49	0.37	0.18	0.47	0.47	0.31	0.46
Post-ranking $\beta^{(j)}_{IPG,p}$	1.30	1.03	1.07	0.23	3.67	3.27	2.53	1.14
	(3.01)	(2.72)	(2.33)	(0.93)	(3.03)	(4.39)	(2.37)	(1.26)
Panel C: Average characteristics within portfolios								
Pre-ranking $\beta^{(j)}_{IPG,p}$	5.62	1.02	-2.64	8.26	14.44	3.10	-8.30	22.74
Market share	0.18	0.20	0.21	-0.03	0.18	0.20	0.21	-0.03
Book-to-market	0.92	0.93	0.88	0.04	0.95	0.94	0.82	0.13

Table 4: **Quarterly exposures of portfolios with respect to macroeconomic growth components**

This table presents first-stage scale-wise betas with respect to industrial production growth risk for three sets of portfolios: Fama and French's (1993) 25 size and book-to-market portfolios; 11 stock and bond portfolios as in Koijen et al. (2013) (the market portfolio (MKT), five book-to-market portfolios and five constant maturity treasury bond portfolios (CMT)); and, 30 quintile portfolios sorted on six different characteristics: size, book-to-market, operating profitability (OP), investment (INV), short-term reversal (STR) and long-term reversal (LTR) (each of these quintile portfolios is an average across size groups, except size itself, which portfolios are an average across book-to-market groups). The betas are estimated component-wise, that is, regressing the high and low frequency component of returns ($R_t^{e,p,(1:4)}$ and $R_t^{e,p,(>4)}$) on the innovation in component of IPG at the same scale ($u_{IPG,t}^{(1:4)}$ and $u_{IPG,t}^{(>4)}$). The associated t-statistics (in parentheses) are based on Newey-West standard errors with 16 lags. The sample period is 1965:Q1 to 2011:Q4.

	High-frequency growth risk ($\beta^{(1:4)}$)						Low-frequency growth risk ($\beta^{(1:4)}$)					
Panel A: 25 Portfolios sorted on size and book-to-market												
Size\BM												
	Growth	BM2	BM3	BM4	Value		Growth	BM2	BM3	BM4	Value	
Small	1.75	1.71	1.38	1.33	1.71		1.43	2.99	3.70	3.37	4.86	
Size2	1.28	1.07	1.11	1.00	1.14		2.80	2.70	3.08	3.85	4.08	
Size3	0.79	0.93	0.89	1.07	0.91		2.77	3.42	3.19	3.52	3.64	
Size4	0.74	0.82	0.90	0.87	1.09		1.88	2.96	3.59	2.86	3.82	
Big	0.42	0.52	0.38	0.67	0.66		2.06	2.61	2.32	2.32	2.95	
Small	(2.28)	(2.46)	(2.24)	(2.55)	(3.08)		(0.59)	(1.63)	(2.15)	(2.03)	(2.93)	
Size2	(2.05)	(1.86)	(2.54)	(2.13)	(2.50)		(1.90)	(2.39)	(2.74)	(3.39)	(3.41)	
Size3	(1.42)	(1.94)	(2.33)	(2.60)	(2.36)		(2.67)	(3.69)	(4.34)	(3.26)	(3.87)	
Size4	(1.68)	(2.09)	(2.49)	(2.22)	(2.21)		(2.17)	(3.95)	(3.80)	(2.99)	(4.02)	
Big	(1.11)	(1.67)	(1.55)	(2.28)	(2.00)		(2.54)	(4.16)	(3.12)	(3.84)	(4.68)	
Panel B: 11 Stock and bond portfolios												
Stocks	Growth	BM2	BM3	BM4	Value	MKT	Growth	BM2	BM3	BM4	Value	MKT
	0.54	0.63	0.53	0.83	0.92	0.60	2.07	2.79	2.72	2.62	3.41	2.53
	(1.39)	(1.93)	(2.02)	(2.45)	(2.39)	(1.88)	(3.01)	(4.60)	(3.74)	(3.51)	(4.90)	(4.79)
Bonds	CMT1	CMT2	CMT5	CMT7	CMT10		CMT1	CMT2	CMT5	CMT7	CMT10	
	-0.06	-0.13	-0.25	-0.32	-0.33		0.45	0.72	1.17	1.19	1.55	
	(-1.47)	(-1.89)	(-1.90)	(-2.18)	(-1.82)		(3.28)	(2.99)	(2.76)	(2.28)	(2.43)	
Panel C: 30 Portfolios sorted on characteristics												
Size	Small	Size2	Size3	Size4	Big		Small	Size2	Size3	Size4	Big	
	1.68	1.21	1.01	0.95	0.54		3.45	3.45	3.45	3.15	2.52	
	(2.68)	(2.43)	(2.38)	(2.37)	(1.89)		(1.92)	(3.05)	(4.00)	(4.09)	(4.45)	
BM	Growth	BM2	BM3	BM4	Value		Growth	BM2	BM3	BM4	Value	
	1.09	1.08	1.00	1.06	1.16		2.33	3.03	3.31	3.34	4.01	
	(2.04)	(2.32)	(2.64)	(2.71)	(2.76)		(2.18)	(3.32)	(3.61)	(3.55)	(4.37)	
LTR	Low	2	3	4	High		Low	2	3	4	High	
	1.71	1.16	0.89	0.95	1.11		4.15	3.91	2.89	3.02	3.20	
	(3.26)	(2.60)	(2.41)	(2.39)	(2.20)		(3.02)	(3.89)	(3.39)	(3.52)	(3.64)	
STR	Low	2	3	4	High		Low	2	3	4	High	
	1.35	1.14	1.06	1.05	1.01		3.67	3.24	3.37	3.24	2.45	
	(2.37)	(2.60)	(2.52)	(2.50)	(2.16)		(2.14)	(3.20)	(4.13)	(3.85)	(2.42)	
OP	Low	2	3	4	High		Low	2	3	4	High	
	1.01	1.00	0.98	1.02	1.18		2.49	2.95	3.35	3.22	3.46	
	(2.20)	(2.49)	(2.65)	(2.36)	(2.31)		(2.33)	(3.37)	(4.18)	(4.06)	(3.63)	
INV	Low	2	3	4	High		Low	2	3	4	High	
	1.24	0.96	0.92	1.02	1.16		3.53	3.52	3.20	2.80	2.78	
	(3.09)	(2.87)	(2.33)	(2.24)	(2.05)		(3.51)	(4.54)	(3.77)	(2.76)	(2.47)	

Table 5: **Macroeconomic growth risk: Cross-sectional regressions for portfolios**
This table reports price of risk estimates from portfolio-level cross-sectional regressions of average excess returns on estimated risk loadings with respect macroeconomic growth risk. The risk loadings are estimated in a first-stage component-wise time-series regression of portfolio returns on innovations in industrial production growth. We focus on high and low frequency components of IPG ($u^{(1:4)}_{IPG,t}$ and $u^{(>4)}_{IPG,t}$) and use three sets of portfolios: Fama and French's (1993) 25 size and book-to-market portfolios in Panel A; in Panel B, 11 stock and bond portfolios as in Koijen et al. (2013) (the market portfolio, five book-to-market portfolios, and five constant maturity treasury bond portfolios); and, in Panel C, 30 quintile portfolios sorted on six different characteristics: size, book-to-market, operating profitability, investment, short-term reversal, and long-term reversal (each of these quintile portfolios is an average across size groups, except size itself, which portfolios are an average across book-to-market groups). We report second-stage risk-price estimates (in percent per year), GMM-corrected t-statistics, R^2, and the mean absolute pricing error (MAPE). The scale-wise exposures are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. As a benchmark, we present results for a risk-neutral asset pricing model as well as for the Fama-French three factor model (FF3M, where we also consider a restricted version that fixes the risk premium at each factor's sample average return). The sample period is 1965:Q1 to 2011:Q4.

	λ_0	$\lambda^{(1:4)}$	$\lambda^{(>4)}$	λ_{MKT}	λ_{SMB}	λ_{HML}	R^2 [MAPE]
Panel A: 25 Size- and book-to-market-sorted portfolios							
Risk Neutral	8.72						0.000
	(2.83)						[2.440]
$j = 1:4$	5.16	1.32					0.176
	(1.92)	(1.44)					[1.928]
$j > 4$	-1.14		2.42				0.693
	(-0.25)		(3.00)				[1.260]
$j = 1:4$ & $j > 4$	-1.87	0.56	2.23				0.715
	(-0.59)	(0.62)	(3.54)				[1.183]
FF3M	12.26			-6.54	2.94	4.92	0.705
	(2.96)			(-1.37)	(1.72)	(2.66)	[1.040]
FF3M-restricted				5.39	3.34	4.64	0.631
				(2.08)	(2.00)	(2.66)	[1.180]
Panel B: The market, 5 book-to-market portfolios, and 5 bond portfolios							
Risk Neutral	4.47						0.000
	(3.06)						[2.339]
$j = 1:4$	3.04	2.58					0.842
	(2.25)	(1.65)					[0.886]
$j > 4$	-0.86		2.66				0.906
	(-0.39)		(1.55)				[0.645]
$j = 1:4$ & $j > 4$	0.39	1.03	1.75				0.933
	(0.68)	(0.84)	(2.83)				[0.501]
FF3M	1.58			4.19	1.07	3.69	0.955
	(2.29)			(1.52)	(0.23)	(1.63)	[0.422]
FF3M-restricted				5.39	3.34	4.64	0.654
				(2.08)	(2.00)	(2.66)	[1.027]
Panel C: 30 Characteristics-sorted portfolios							
Risk Neutral	8.63						0.000
	(2.78)						[1.570]
$j = 1:4$	3.67	0.98					0.199
	(1.30)	(2.08)					[1.357]
$j > 4$	-3.47		1.66				0.643
	(-0.66)		(2.96)				[0.905]
$j = 1:4$ & $j > 4$	-3.52	0.05	1.64				0.630
	(-1.05)	(0.09)	(3.41)				[0.895]
FF3M	-2.51			7.58	3.38	7.18	0.628
	(-0.62)			(1.68)	(2.02)	(3.76)	[0.869]
FF3M-restricted				5.39	3.34	4.64	0.534
				(2.08)	(2.00)	(2.66)	[0.976]

Table 6: **Simulation**

This table presents results from the simulation exercise described in Section 3.3. We simulate 500 pseudo-samples of macroeconomic growth, which follows an AR(1)-process with moments matched to realized industrial production growth. From these artificial growth series we extract the components at scale $j = 1:4$ and $j > 4$. Then, we run our asset pricing tests using realized returns on individual stocks and three sets of portfolios: 25 size and book-to-market portfolios in Panel A (25P); in Panel B, the market portfolio, five book-to-market portfolios, and five constant maturity treasury bond portfolios (11P); and, in Panel C, 30 quintile portfolios sorted on six different characteristics (30P). For individual stocks, we run quarterly cross-sectional regressions of returns on lagged scale-wise risk exposures, estimated over a five-year rolling window. For portfolios, we run a cross-sectional regression of average returns on scale-wise risk exposures estimated over the full pseudo-sample. In Panel A of this table we present percentiles (in **bold**) of the simulated distribution of risk-prices $\lambda^{b(\cdot)}$. In Panel B we present two-sided rejection rates at the 5%-level (using Fama and MacBeth (1973) standard errors at the stock-level and GMM standard errors at the portfolio-level). At the bottom of this panel, we present joint rejection rates. This fraction is the percentage of pseudo-samples in which the risk premium is (i) consistent in sign and (ii) significant in multiple cross-sections.

Panel A: Percentiles of simulated prices of risk

	Stocks		25P		11P		30P	
	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$
1	-1.36	-1.72	-2.69	-3.34	-4.65	-4.58	-1.76	-1.97
2.5	-1.08	-1.46	-2.06	-2.57	-3.15	-3.34	-1.40	-1.75
5	-0.95	-1.22	-1.85	-2.28	-2.91	-2.89	-1.31	-1.63
20	-0.48	-0.59	-1.04	-1.46	-2.03	-1.87	-0.72	-1.07
50	-0.05	0.05	0.05	-0.12	0.01	-0.22	0.15	-0.07
80	0.45	0.71	1.33	1.41	1.85	1.68	0.96	0.87
95	0.94	1.32	2.02	2.09	2.96	2.67	1.40	1.45
97.5	1.08	1.46	2.32	2.47	3.29	3.38	1.61	1.66
99	1.47	1.97	2.84	2.72	4.27	4.68	1.94	1.95

Panel B: Separate and joint rejection rates in asset pricing tests

	Stocks		25P		11P		30P	
	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$
Reject H_0, $\lambda^{b(\cdot)} < 0$	0.032	0.048	0.182	0.276	0.184	0.222	0.210	0.316
Reject H_0, $\lambda^{b(\cdot)} > 0$	0.020	0.058	0.228	0.224	0.200	0.186	0.276	0.264
Reject H_0	0.052	0.106	0.410	0.500	0.384	0.408	0.486	0.580

	Significant: stocks + 1 set of portfolios		Significant: stocks + 2 sets of portfolios		All significant	
	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$	$\lambda^{b(1:4)}$	$\lambda^{b(>4)}$
Reject H_0, $\lambda^{b(\cdot)} < 0$	0.022	0.040	0.002	0.020	0.002	0.012
Reject H_0, $\lambda^{b(\cdot)} > 0$	0.016	0.048	0.010	0.032	0.004	0.012
Reject H_0	0.038	0.088	0.012	0.052	0.006	0.024

Table 7: **Comparison with long-run risk model**
This table reports risk-price estimates from cross-sectional regressions of portfolio-level average excess returns on estimated risk loadings from a regression of: (i) the long-term component of returns on the long-term component of macroeconomic risk, denoted $\beta^{(>4)}$; or, (ii) one-period returns on the long-run consumption growth rate, as is standard in the long-run risk literature, denoted β_{LRR}. We focus on three different sets of portfolios in Panel A to C: Fama and French's (1993) 25 size and book-to-market portfolios; the market portfolio, five book-to-market portfolios, and five constant maturity treasury bond portfolios (as in Koijen et al. (2013); and, 30 quintile portfolios sorted on six different characteristics: size, book-to-market, operating profitability, investment, short-term reversal, and long-term reversal. We report second-stage risk-price estimates (in percent per year), GMM-corrected t-statistics, R^2, and the mean absolute pricing error (MAPE). For the sake of comparison, both $\beta^{(>4)}$ and β_{LRR} are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure.

	λ_0	$\lambda^{(>4)}$	λ_{LRR}	R^2 [MAPE]
Panel A: 25 Size- and book-to-market-sorted portfolios				
$\beta^{(>4)}$	-0.21	2.04		0.48
	(-0.05)	(2.65)		[1.65]
β_{LRR}	5.57		1.26	0.17
	(1.38)		(1.82)	[1.94]
$\beta^{(>4)}$ & β_{LRR}	-0.63	2.46	-0.65	0.48
	(-0.17)	(4.75)	(-1.73)	[1.61]
Panel B: The market, 5 book-to-market portfolios, and 5 bond portfolios				
$\beta^{(>4)}$	0.55	2.54		0.82
	(0.42)	(1.64)		[0.84]
β_{LRR}	1.54		2.34	0.70
	(0.94)		(0.99)	[1.06]
$\beta^{(>4)}$ & β_{LRR}	0.45	2.88	-0.40	0.80
	(0.43)	(1.94)	(-0.57)	[0.79]
Panel C: 30 Characteristics-sorted portfolios				
$\beta^{(>4)}$	-3.83	1.68		0.66
	(-0.68)	(2.44)		[0.94]
β_{LRR}	1.90		1.50	0.55
	(0.36)		(2.07)	[0.97]
$\beta^{(>4)}$ & β_{LRR}	-2.97	1.38	0.28	0.65
	(-0.79)	(2.89)	(0.66)	[0.91]

Table 8: **Macroeconomic volatility risk: Cross-sectional regressions for individual stocks** The table is analogous to Table 2 and reports second-stage cross-sectional regressions of quarterly excess returns of individual stocks on lagged volatility risk loadings. The risk loadings are first-stage betas estimated using a five-year rolling window component-wise time-series regression of the j-th component of excess returns on the innovation in the j-th component of conditional IPG volatility ($u^{(j)}_{IPVOL,t}$, Panel A) or the innovation in the components of the out-of-sample IPG volatility series ($u^{(j)}_{IPVOL-OOS,t}$, Panel B). IPVOL is estimated using an AR(1)-GARCH(1,1) model over the full sample, whereas IPVOL-OOS is estimated in each quarter t using only historical data over an expanding window starting from 1926Q3. In Panel A, we also control for characteristics and short- and long-term exposures to the three factors of Fama and French (1993). We report time-series averages of the second-stage risk-price estimates (in percent per year), with Fama and MacBeth (1973) t-statistics presented underneath in parenthesis, as well as the cross-sectional R^2. The scale-wise exposures are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in volatility risk exposure. The sample period is 1965.Q1 to 2011.Q4.

Panel A: Macro-volatility risk ($u^{(1:4)}_{IPGVOL,t}$ & $u^{(>4)}_{IPGVOL,t}$) vs. characteristics and Fama-French factors												
	λ_0	$\lambda^{(1:4)}_{vol}$	$\lambda^{(>4)}_{vol}$	γ_{SIZE}	γ_{BM}	λ^1_{MKT}	λ^1_{SMB}	λ^1_{HML}	λ^{16}_{MKT}	λ^{16}_{SMB}	λ^{16}_{HML}	R^2
$j = 1:4$	9.31	0.38										0.008
	(3.06)	(0.59)										
$j > 4$	9.67		-1.58									0.011
	(3.19)		(-2.16)									
$j = 1:4$ & $j > 4$	8.37	0.88	-2.07									0.018
	(2.93)	(1.35)	(-2.82)									
$SIZE^i_t$, BM^i_t	9.22	0.29	-1.46	-2.54	1.62							0.048
	(3.13)	(0.54)	(-2.48)	(-2.38)	(2.47)							
β^1_{MKT}, β^1_{SMB}, β^1_{HML}	6.92	-0.51	-1.76			1.34	1.69	0.85				0.049
	(3.39)	(-0.90)	(-2.70)			(1.18)	(1.71)	(1.33)				
β^{16}_{MKT}, β^{16}_{SMB}, β^{16}_{HML}	8.78	0.63	-1.96						-0.43	-0.20	-0.02	0.030
	(3.21)	(0.99)	(-2.02)						(-1.36)	(-1.08)	(-0.12)	

Panel B: Out-of-sample macro volatility risk ($u^{(1:4)}_{IPGVOL-OOS,t}$ & $u^{(>4)}_{IPGVOL-OOS,t}$)				
	λ_0	$\lambda^{(1:4)}_{vol}$	$\lambda^{(>4)}_{vol}$	R^2
$j = 1:4$	9.32	0.50		0.009
	(3.06)	(0.77)		
$j > 4$	9.68		-1.73	0.011
	(3.19)		(-2.39)	
$j = 1:4$ & $j > 4$	8.38	1.04	-2.27	0.019
	(2.93)	(1.56)	(-3.12)	

Table 9: **Quarterly exposures of portfolios with respect to macroeconomic volatility components**

This table presents first-stage scale-wise exposures to industrial production volatility risk (estimated with an AR(1)-GARCH(1,1) process for IPG) for three sets of portfolios: Fama and French's (1993) 25 size and book-to-market portfolios; 11 stock and bond portfolios as in Koijen et al. (2013) (the market portfolio (MKT), five book-to-market portfolios and five constant maturity treasury bond portfolios (CMT)); and, 30 quintile portfolios sorted on six different characteristics: size, book-to-market, operating profitability (OP), investment (INV), short-term reversal (STR) and long-term reversal (LTR) (each of these quintile portfolios is an average across size groups, except size itself, which portfolios are an average across book-to-market groups). The scale-wise exposures, denoted $\delta^{(j)}$, are estimated component-wise, that is, regressing the high and low frequency component of returns ($R_t^{e,p,(1:4)}$ and $R_t^{e,p,(>4)}$) on innovations in the component of conditional volatility of industrial production growth at the same scale ($u_{IPVOL,t}^{(1:4)}$ and $u_{IPVOL,t}^{(>4)}$). The associated t-statistics are based on Newey-West standard errors with 16 lags. The sample period is 1965:Q1 to 2011:Q4.

	High-frequency volatility risk ($\delta^{(1:4)}$)						Low-frequency volatility risk ($\delta^{(>4)}$)					
Panel A: 25 Portfolios sorted on size and book-to-market												
Size\BM												
	Growth	BM2	BM3	BM4	Value		Growth	BM2	BM3	BM4	Value	
Small	3.88	3.47	2.67	2.44	3.13		-9.37	-12.08	-14.55	-15.54	-17.67	
Size2	3.20	2.75	2.19	2.30	2.00		-5.64	-8.34	-11.64	-14.71	-15.46	
Size3	2.42	2.08	1.98	2.06	2.64		-7.01	-11.22	-9.29	-11.22	-13.50	
Size4	2.07	1.49	1.19	1.39	0.73		-4.29	-8.59	-13.02	-10.28	-14.90	
Big	1.68	0.72	-0.31	0.53	0.30		-3.04	-6.49	-10.34	-8.68	-10.43	
Small	(0.91)	(0.85)	(0.66)	(0.64)	(0.60)		(-1.45)	(-2.45)	(-3.09)	(-3.04)	(-3.59)	
Size2	(0.84)	(0.72)	(0.63)	(0.62)	(0.44)		(-1.13)	(-2.33)	(-3.76)	(-3.83)	(-3.89)	
Size3	(0.70)	(0.60)	(0.70)	(0.58)	(0.71)		(-1.75)	(-3.46)	(-4.36)	(-3.90)	(-5.03)	
Size4	(0.68)	(0.47)	(0.35)	(0.40)	(0.18)		(-1.08)	(-2.51)	(-2.43)	(-3.08)	(-3.23)	
Big	(0.69)	(0.33)	(-0.13)	(0.16)	(0.12)		(-0.81)	(-2.08)	(-2.81)	(-2.13)	(-3.69)	
Panel B: 11 Stock and bond portfolios												
Stocks	Growth	BM2	BM3	BM4	Value	MKT	Growth	BM2	BM3	BM4	Value	MKT
	1.79	0.99	0.26	0.96	1.55	1.12	-3.02	-7.29	-11.05	-10.09	-12.53	-7.36
	(0.70)	(0.40)	(0.10)	(0.27)	(0.43)	(0.41)	(-0.84)	(-2.43)	(-3.08)	(-2.60)	(-4.63)	(-2.25)
Bonds	CMT1	CMT2	CMT5	CMT7	CMT10		CMT1	CMT2	CMT5	CMT7	CMT10	
	0.35	0.46	0.66	0.80	1.04		-0.64	-1.06	-1.86	-1.74	-2.54	
	(2.76)	(2.22)	(1.54)	(1.71)	(1.83)		(-0.97)	(-0.94)	(-1.01)	(-0.80)	(-1.02)	
Panel C: 30 Portfolios sorted on characteristics												
Size	Small	Size2	Size3	Size4	Big		Small	Size2	Size3	Size4	Big	
	2.88	2.28	2.05	1.16	0.64		-14.16	-11.56	-10.74	-10.15	-7.57	
	(0.61)	(0.53)	(0.55)	(0.30)	(0.22)		(-2.90)	(-3.33)	(-3.90)	(-2.65)	(-2.29)	
BM	Growth	BM2	BM3	BM4	Value		Growth	BM2	BM3	BM4	Value	
	2.50	2.03	1.38	1.56	1.53		-6.07	-9.72	-11.96	-12.18	-14.26	
	(0.67)	(0.55)	(0.39)	(0.39)	(0.35)		(-1.50)	(-2.88)	(-3.48)	(-3.36)	(-4.19)	
LTR	Low	2	3	4	High		Low	2	3	4	High	
	4.30	2.35	1.74	1.76	1.68		-7.91	-11.89	-10.58	-10.46	-9.83	
	(0.84)	(0.57)	(0.49)	(0.49)	(0.41)		(-1.41)	(-3.25)	(-3.38)	(-3.54)	(-2.54)	
STR	Low	2	3	4	High		Low	2	3	4	High	
	2.66	2.08	1.64	1.55	0.99		-13.24	-11.67	-10.92	-8.96	-7.56	
	(0.47)	(0.48)	(0.44)	(0.45)	(0.30)		(-2.00)	(-2.94)	(-3.25)	(-2.89)	(-2.17)	
OP	Low	2	3	4	High		Low	2	3	4	High	
	1.41	1.58	1.38	2.11	2.62		-8.24	-9.88	-10.76	-9.94	-9.95	
	(0.35)	(0.43)	(0.37)	(0.56)	(0.66)		(-2.19)	(-3.12)	(-3.01)	(-2.96)	(-2.59)	
INV	Low	2	3	4	High		Low	2	3	4	High	
	1.40	1.64	1.79	2.13	2.25		-10.55	-10.92	-10.90	-10.55	-7.97	
	(0.34)	(0.47)	(0.50)	(0.56)	(0.56)		(-2.80)	(-2.80)	(-3.24)	(-2.89)	(-2.12)	

Table 10: **Macroeconomic volatility risk: Cross-sectional regressions for portfolios**
The table is analogous to Table 5, replacing the components of industrial production growth with the components of conditional industrial production volatility (IPVOL). IPVOL is estimated using an AR(1)-GARCH(1,1) process for IPG. The table reports risk-price estimates (in percent per year) from cross-sectional regressions of portfolio-level average excess returns on estimated risk loadings with respect to innovations in the high and low frequency components of IPVOL ($u^{(1:4)}_{IPVOL,t}$ and $u^{(>4)}_{IPVOL,t}$). The risk loadings are estimated in a first stage component-wise time-series regression of portfolio returns on the respective component of the first-difference in conditional volatility. We focus on three sets of portfolios: Fama and French's (1993) 25 size and book-to-market portfolios; 11 stock and bond portfolios as in Koijen et al. (2013) (the market portfolio, five book-to-market portfolios and five constant maturity treasury bond portfolios); and, 30 quintile portfolios sorted on six different characteristics: size, book-to-market, operating profitability, investment, short-term reversal and long-term reversal. We report second-stage risk-price estimates, GMM-corrected t-statistics, R^2 and the mean absolute pricing error (MAPE). The scale-wise exposures are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in volatility risk exposure. The sample period is 1965:Q1 to 2011:Q4.

	λ_0	$\lambda^{(1:4)}_{vol}$	$\lambda^{(>4)}_{vol}$	R^2 [MAPE]
Panel A: 25 Size- and book-to-market-sorted portfolios				
$j = 1:4$	6.96	0.92		0.063
	(2.44)	(0.98)		[2.163]
$j > 4$	2.17		-2.29	0.613
	(0.63)		(-3.10)	[1.393]
$j = 1:4$ & $j > 4$	1.19	0.64	-2.21	0.648
	(0.44)	(0.74)	(-3.38)	[1.188]
Panel B: The market, 5 book-to-market portfolios, and 5 bond portfolios				
$j = 1:4$	1.74	1.43		0.182
	(1.28)	(0.67)		[2.084]
$j > 4$	1.25		-2.63	0.880
	(1.32)		(-2.10)	[0.689]
$j = 1:4$ & $j > 4$	-0.09	0.84	-2.42	0.970
	(-0.08)	(1.50)	(-2.34)	[0.318]
Panel C: 30 Characteristics-sorted portfolios				
$j = 1:4$	5.78	1.03		0.222
	(1.36)	(1.70)		[1.313]
$j > 4$	0.37		-1.51	0.522
	(0.10)		(-3.75)	[0.937]
$j = 1:4$ & $j > 4$	-1.97	0.94	-1.46	0.730
	(-0.64)	(2.62)	(-4.67)	[0.739]

Table 11: **Macroeconomic risk: Growth or volatility?**
This table reports risk-price estimates (in percent per year) from cross-sectional regressions of excess returns on growth and volatility risk loadings. Risk loadings for this two-factor model are obtained from two separate scale-wise time-series regressions of the long-term component of returns on (i) the long-term component of industrial production growth, i.e., $\beta_{i,t}^{(>4)}$, and (ii) the long-term component of industrial production volatility, i.e., $\delta_{i,t}^{(>4)}$. We consider both stock-level tests (Panel A), where the loadings are estimated over a five-year historical rolling window, and portfolio-level tests (Panels B to C), where the loadings are estimated over the full sample. We consider three sets of portfolios: Fama and French's (1993) 25 size and book-to-market portfolios; 11 stock and bond portfolios as in Koijen et al. (2013) (the market portfolio, five book-to-market portfolios and five constant maturity treasury bond portfolios); and, 30 quintile portfolios sorted on six different characteristics: size, book-to-market, operating profitability, investment, short-term reversal and long-term reversal. For the stock-level test, we report time-series averages of the second-stage risk-price estimates, with Fama and MacBeth (1973) t-statistics presented underneath in parenthesis, as well as the cross-sectional R^2. For the portfolio-level tests, we report second-stage risk-price estimates, GMM-corrected t-statistics (in parenthesis), R^2, and the mean absolute pricing error (MAPE). The scale-wise exposures to macroeconomic risk are normalized so that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. The sample period is 1965:Q1 to 2011:Q4.

$$R_{t+1}^{e,i} = \lambda_{0,t} + \lambda_{growth,t}^{(>4)}\beta_{i,t}^{(>4)} + \lambda_{vol,t}^{(>4)}\delta_{i,t}^{(>4)} + \alpha_{i,t+1}$$

λ_0	$\lambda_{growth}^{(>4)}$	$\lambda_{vol}^{(>4)}$	R^2 [MAPE]
Panel A: Individual stocks			
8.76	1.57	-1.29	0.018
(3.03)	(1.96)	(-1.42)	
Panel B: 25 Size- and book-to-market-sorted portfolios			
-0.71	1.67	-0.93	0.716
(-0.20)	(3.39)	(-1.27)	[1.213]
Panel C: The market, 5 book-to-market portfolios, and 5 bond portfolios			
-0.15	1.62	-1.12	0.922
(-0.10)	(0.97)	(-0.99)	[0.571]
Panel D: 30 Characteristics-sorted portfolios			
-4.06	1.18	-0.75	0.713
(-1.09)	(3.94)	(-3.00)	[0.844]

Internet Appendix

This Internet Appendix presents a range of robustness checks for the results in the paper.

Table IA.1: **Is the result driven by long-run returns, or (innovations in) long-run growth, or both?**

This table reports risk-price estimates from cross-sectional regressions of portfolio-level average excess returns on estimated risk loadings from three alternative consumption-based models. These models combine elements from our scale-specific risk measure ($\beta^{(>4)}$) and from the long-run risk measure (β^{LRR}, see Table 7 of the paper). The first model estimates risk loadings as in the Consumption-CAPM (β_{CCAPM}), by regressing one quarter excess returns on one quarter consumption growth. The second model estimates risk loadings as in a four-year consumption CAPM (β^{4Y}_{CCAPM}), by regressing four-year returns (the left-hand side when estimating our scale-specific consumption risk measure) on four-year consumption growth (the right-hand side when estimating the long-run risk measure). The third model is a hybrid and takes the left-hand side from the long-run risk regression (current one quarter excess log returns) and regresses this on the right-hand side from our scale-specific long-term consumption risk measure (the innovation in future four-year consumption growth) and is denoted β_{hybrid}. Models four to six run a horse race for these risk measures with $\beta^{(>4)}$. We report second-stage risk-price estimates (in percent per year), GMM-corrected t-statistics, R^2, and the mean absolute pricing error (MAPE). For the sake of comparison, all exposures are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure.

	Panel A: 25 Size- and book-to-market-sorted portfolios						Panel B: The market, 5 book-to-market portfolios, and 5 bond portfolios						Panel C: 30 Characteristics-sorted portfolios					
	λ_0	$\lambda^{(>4)}$	λ_{CCAPM}	λ^{4Y}_{CCAPM}	λ_{hybrid}	R^2	λ_0	$\lambda^{(>4)}$	λ_{CCAPM}	λ^{4Y}_{CCAPM}	λ_{hybrid}	R^2	λ_0	$\lambda^{(>4)}$	λ_{CCAPM}	λ^{4Y}_{CCAPM}	λ_{hybrid}	R^2
β_{CCAPM}	5.33		0.82			0.041	2.81		2.50			0.784	7.26		0.17			-0.028
	(1.65)		(0.92)			[2.241]	(2.20)		(1.38)			[1.028]	(2.80)		(0.39)			[1.569]
β^{4Y}_{CCAPM}	6.82			0.80		0.036	2.79			2.48		0.769	5.33			1.16		0.293
	(2.17)			(1.77)		[2.222]	(3.02)			(1.92)		[1.041]	(1.78)			(4.22)		[1.201]
β_{hybrid}	8.34				-0.47	-0.013	1.90				-2.15	0.574	8.68				0.37	-0.001
	(2.45)				(-0.54)	[2.302]	(0.76)				(-1.28)	[1.415]	(2.30)				(0.82)	[1.488]
$\beta^{>4}$ vs. β_{CCAPM}	-0.62	1.99	0.15			0.459	0.96	2.07	0.49			0.794	-1.68	1.80	-0.39			0.677
	(-0.20)	(3.22)	(0.17)			[1.634]	(2.09)	(1.75)	(0.31)			[0.845]	(-0.59)	(4.86)	(-0.85)			[0.915]
$\beta^{>4}$ vs. β^{4Y}_{CCAPM}	-0.25	2.34		-0.53		0.482	1.22	1.70		0.91		0.813	-3.45	1.54		0.24		0.652
	(-0.07)	(4.66)		(-1.82)		[1.655]	(1.35)	(1.25)		(1.08)		[0.857]	(-1.02)	(3.95)		(1.08)		[0.922]
$\beta^{>4}$ vs. β_{hybrid}	0.04	1.94			-0.15	0.461	0.25	1.90			-1.06	0.921	-3.44	1.61			0.08	0.644
	(0.01)	(3.76)			(-0.18)	[1.633]	(0.24)	(1.32)			(-1.75)	[0.539]	(-0.89)	(4.62)			(0.18)	[0.954]

Table IA.2: **Robustness checks for the methodology**
This table presents three robustness checks for the methodology used to obtain our estimates of the price of high (scale $j = 1:4$) and low ($j > 4$) frequency macro-growth risk among individual stocks in Table 2. In Panel A and Panel B we estimate betas over a six- and ten-year rolling window, respectively, in contrast to the five-year rolling window used in the main analysis. This naturally changes the inclusion requirement: stocks need to have available the last ten and fourteen years of returns, respectively, in contrast to the nine years used in the main analysis of Table 2. In Panel C, we update component-wise exposures only once a year (at year-end).

	λ_0	$\lambda^{(1:4)}$	$\lambda^{(>4)}$	γ_{SIZE}	γ_{BM}	R^2
Panel A: 6 + 4 years inclusion requirement						
$j = 1:4$	9.56	1.19				0.008
	(3.13)	(2.07)				
$j > 4$	8.83		2.40			0.010
	(2.94)		(3.57)			
$j = 1:4$ & $j > 4$	8.73	0.99	1.95			0.017
	(2.98)	(1.77)	(2.90)			
$j = 1:4$ & $j > 4$	9.40	0.18	1.75	-2.77	1.48	0.046
	(3.13)	(0.41)	(3.43)	(-2.66)	(2.33)	
Panel B: 10 + 4 years inclusion requirement						
$j = 1:4$	9.08	1.18				0.010
	(3.26)	(1.90)				
$j > 4$	8.47		1.61			0.010
	(2.88)		(2.65)			
$j = 1:4$ & $j > 4$	8.11	0.61	1.51			0.018
	(2.91)	(0.99)	(2.55)			
$j = 1:4$ & $j > 4$	8.93	-0.17	1.32	-2.44	1.59	0.046
	(3.12)	(-0.37)	(2.83)	(-2.62)	(2.62)	
Panel C: Annual rebalancing at the end of Q4						
$j = 1:4$	9.68	1.31				0.009
	(3.17)	(2.26)				
$j > 4$	8.99		2.25			0.010
	(2.96)		(3.38)			
$j = 1:4$ & $j > 4$	8.75	1.30	1.85			0.016
	(3.00)	(2.21)	(2.78)			
$j = 1:4$ & $j > 4$	9.40	0.60	1.51	-2.78	1.90	0.045
	(3.13)	(1.29)	(2.77)	(-2.64)	(3.26)	

Table IA.3: **Macroeconomic growth risk: Cross-sectional regressions for individual stocks at the monthly frequency**

This table reports second-stage cross-sectional regressions of monthly excess stock returns on lagged estimated risk loadings. The risk loadings are first-stage component-wise betas estimated with a five-year rolling regression of the j-th component of excess returns on the innovation in the j-th component of industrial production growth ($u^{(j)}_{IPG,t}$). With monthly data, we focus on the combined scale $j = 1:5$, capturing variation with a half-life ranging from one month to 2.7 years, and $j > 5$, capturing variation with a half-life larger than 2.7 years. Panel B presents the trade-off between high and low frequency risk with controls. The first model controls for characteristics, i.e., size ($SIZE^i_t$) and book-to-market (BM^i_t), with prices denoted γ_{SIZE} and γ_{BM}, respectively. In models three and four, we control for exposure to the three factors of Fama and French (1993) estimated over a five-year rolling window of monthly returns (as is standard in the literature) and overlapping four-year returns, respectively, denoted: β^1_X and β^{48}_X, where X=MKT,SMB,HML. We report time-series averages of the second-stage price of risk estimates (in percent per year), with Fama and MacBeth (1973) t-statistics presented underneath in parenthesis, as well as the cross-sectional R^2. The scale-wise exposures are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. The sample period is January 1965 to December 2011.

Panel A: The price of exposure to macro-growth risk across scales ($u^{(j)}_{IPG,t}$)

	λ_0	$\lambda^{(1)}$	$\lambda^{(2)}$	$\lambda^{(3)}$	$\lambda^{(4)}$	$\lambda^{(5)}$	$\lambda^{(1:5)}$	$\lambda^{(>5)}$	R^2
$j = 1:5$	9.69						0.93		0.003
	(3.65)						(2.26)		
$j > 5$	8.47							2.15	0.008
	(3.27)							(3.47)	
$j = 1:5$ & $j > 5$	8.38						0.76	1.98	0.011
	(3.36)						(1.93)	(3.23)	
All	8.35	-0.04	-0.01	1.05	0.41	-1.05		2.15	0.024
	(3.84)	(-0.11)	(-0.03)	(2.12)	(0.72)	(-1.99)		(3.60)	

Panel B: Scale-wise growth risk ($j = 1:5$ & $j > 5$) vs. characteristics and Fama-French factors

Controls	λ_0	$\lambda^{(1:5)}$	$\lambda^{(>5)}$	γ_{SIZE}	γ_{BM}	λ^1_{MKT}	λ^1_{SMB}	λ^1_{HML}	λ^{48}_{MKT}	λ^{48}_{SMB}	λ^{48}_{HML}	R^2
$SIZE^i_t$, BM^i_t	9.01	0.66	1.49	-3.12	1.66							0.031
	(3.44)	(1.98)	(2.84)	(-3.19)	(2.85)							
β^1_{MKT}, β^1_{SMB}, β^1_{HML}	6.75	0.09	1.49			0.93	1.73	1.63				0.043
	(4.45)	(0.31)	(3.04)			(0.65)	(1.63)	(1.72)				
β^{48}_{MKT}, β^{48}_{SMB}, β^{48}_{HML}	8.75	0.57	3.32						-1.19	-0.16	0.43	0.023
	(3.86)	(1.59)	(3.76)						(-2.56)	(-0.61)	(1.36)	

Table IA.4: **Alternative measures of growth: Cross-sectional regressions for individual stocks**

This table is similar to Table 2, but replaces industrial production growth with (i) non-durables and services consumption growth (CG) or (ii) a composite measure of macroeconomic growth (CRAG), defined as the first principal component extracted from the growth rates of industrial production, consumption, employment and unemployment. This table reports second-stage cross-sectional regressions of quarterly excess stock returns on lagged estimated risk loadings. The risk loadings are first-stage component-wise betas estimated with a five-year rolling regression of the j-th component of excess returns on the innovation in the j-th component of CG ($u^{(j)}_{CG,t}$, Panel A), or the innovation in the j-th component of CRAG ($u^{(j)}_{CRAG,t}$, Panel B). We also control for characteristics and short- and long-term exposures to the factors of Fama and French (1993). We report time-series averages of the second-stage price of risk estimates (in percent per year), with Fama and MacBeth (1973) t-statistics presented underneath in parenthesis, as well as the cross-sectional R^2. The scale-wise exposures are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. The sample period is 1965.Q1 to 2011.Q4.

Panel A: Scale-wise consumption growth risk ($u^{(j)}_{CG,t}$) vs. characteristics and Fama-French factors

	λ_0	$\lambda^{(1:4)}$	$\lambda^{(>4)}$	γ_{SIZE}	γ_{BM}	λ^1_{MKT}	λ^1_{SMB}	λ^1_{HML}	λ^{16}_{MKT}	λ^{16}_{SMB}	λ^{16}_{HML}	R^2
$j = 1:4$	9.80	0.48										0.008
	(3.27)	(0.82)										
$j > 4$	9.30		1.81									0.010
	(3.04)		(2.71)									
$j = 1:4$ & $j > 4$	9.01	0.51	1.57									0.017
	(3.15)	(0.87)	(2.36)									
$SIZE^i_t$, BM^i_t	9.52	0.33	1.36	-2.83	1.61							0.048
	(3.24)	(0.67)	(2.50)	(-2.59)	(2.45)							
β^1_{MKT}, β^1_{SMB}, β^1_{HML}	6.89	0.11	1.30			1.29	1.63	0.99				0.050
	(3.37)	(0.22)	(2.17)			(1.12)	(1.61)	(1.52)				
β^{16}_{MKT}, β^{16}_{SMB}, β^{16}_{HML}	9.34	0.61	1.80						-0.73	0.08	-0.04	0.030
	(3.44)	(1.09)	(2.03)						(-2.24)	(0.40)	(-0.19)	

Panel B: Scale-wise composite real activity growth risk ($u^{(j)}_{CRAG,t}$) vs. characteristics and Fama-French factors

	λ_0	$\lambda^{(1:4)}$	$\lambda^{(>4)}$	γ_{SIZE}	γ_{BM}	λ^1_{MKT}	λ^1_{SMB}	λ^1_{HML}	λ^{16}_{MKT}	λ^{16}_{SMB}	λ^{16}_{HML}	R^2
$j = 1:4$	9.46	1.13										0.010
	(3.21)	(1.68)										
$j > 4$	8.80		2.43									0.011
	(2.91)		(3.58)									
$j = 1:4$ & $j > 4$	8.51	0.95	2.08									0.020
	(3.05)	(1.36)	(2.96)									
$SIZE^i_t$, BM^i_t	9.33	0.45	1.87	-2.62	1.58							0.049
	(3.23)	(0.80)	(3.36)	(-2.51)	(2.45)							
β^1_{MKT}, β^1_{SMB}, β^1_{HML}	6.74	-0.21	1.88			1.48	1.65	0.97				0.051
	(3.32)	(-0.42)	(3.10)			(1.25)	(1.72)	(1.51)				
β^{16}_{MKT}, β^{16}_{SMB}, β^{16}_{HML}	8.99	1.09	2.55						-0.83	0.08	-0.10	0.033
	(3.38)	(1.65)	(2.89)						(-2.72)	(0.38)	(-0.53)	

Table IA.5: **Alternative measures of growth: Portfolio sorts**

This table presents portfolio sorts and is similar to Table 3, but replaces industrial production growth with (i) non-durables and services consumption growth (CG, Panel A) or (ii) a composite measure of macroeconomic growth (CRAG, Panel B), defined as the first principal component extracted from the growth rates of industrial production, consumption, employment and unemployment. We present quintile portfolios sorted on exposure to either high ($j = 1 : 4$, columns one to four) or low ($j > 4$, columns five to eight) frequency risk. We report the annualized performance (average return, standard deviation, and Sharpe ratio) and post-ranking beta of equal-weighted (Panel A) and value-weighted (Panel B) portfolios. The post-ranking beta is estimated with a component-wise regression of portfolio returns on innovations in the respective component of CG and CRAG ($u^{(1:4)}_{CG,t}$ or $u^{(>4)}_{CG,t}$, and $u^{(1:4)}_{CRAG,t}$ or $u^{(>4)}_{CRAG,t}$), with t-statistic calculated using Newey and West (1987) standard errors with $2^4 = 16$ lags. Panel C presents pre-ranking beta, market share, and book-to-market ratio, which are averaged within portfolio and over time. To conserve space, we report results only for the first, third and fifth quintile as well as for the High-minus-Low spreading portfolio. The sample period is 1965:Q1 to 2011:Q4.

	High frequency risk ($u^{(1:4)}_{CG,t}$, $u^{(1:4)}_{CRAG,t}$)				Low frequency risk ($u^{(>4)}_{CG,t}$, $u^{(>4)}_{CRAG,t}$)			
	High	Mid	Low	**High-Low**	High	Mid	Low	**High-Low**
Panel A: Consumption growth								
Avg. Ret.	9.43	9.44	9.54	-0.11	11.42	9.23	8.16	3.26
	(2.48)	(3.34)	(3.20)	(-0.07)	(3.01)	(3.29)	(2.53)	(2.17)
Std. Dev.	26.04	19.40	20.41	9.88	25.98	19.22	22.15	10.30
Sharpe	0.36	0.49	0.47	-0.01	0.44	0.48	0.37	0.32
Post-ranking $\beta^{(j)}_{CG,p}$	0.07	0.05	0.05	0.02	0.19	0.15	0.09	0.11
	(3.56)	(3.67)	(4.42)	(1.51)	(5.03)	(4.52)	(1.72)	(4.22)
Panel B: Composite measure of real activity								
Avg. Ret.	10.10	9.89	8.48	1.62	12.04	9.55	7.07	4.96
	(2.65)	(3.39)	(2.93)	(1.01)	(3.23)	(3.43)	(2.14)	(3.43)
Std. Dev.	26.16	20.04	19.84	10.98	25.52	19.08	22.67	9.93
Sharpe	0.39	0.49	0.43	0.15	0.47	0.50	0.31	0.50
Post-ranking $\beta^{(j)}_{CRAG,p}$	0.04	0.03	0.03	0.01	0.08	0.07	0.05	0.03
	(3.51)	(2.97)	(3.90)	(2.45)	(5.03)	(5.34)	(2.40)	(2.14)

Table IA.6: **Alternative measures of growth: Portfolio-level tests**

This table is the equivalent of Table 5 replacing industrial production growth with (i) non-durables and services consumption growth (CG) or (ii) a composite measure of macroeconomic growth (CRAG), defined as the first principal component extracted from the growth rates of industrial production, consumption, employment and unemployment. The table reports risk premium estimates from cross-sectional regressions of portfolio-level average excess returns on estimated scale-wise risk exposures. The risk loadings are estimated in a first stage component-wise time-series regression of portfolio returns on the innovations in the components of CG ($u^{(j)}_{CG,t}$) or CRAG ($u^{(j)}_{CRAG,t}$). We focus on high and low frequency components $j = 1:4$ and $j > 4$ and use three sets of portfolios: Fama and French's (1993) 25 size and book-to-market portfolios in Panel A; in Panel B, 11 stock and bond portfolios as in Koijen et al. (2013) (the market portfolio, five book-to-market portfolios, and five constant maturity treasury bond portfolios); and, in Panel C, 30 quintile portfolios sorted on six different characteristics: size, book-to-market, operating profitability, investment, short-term reversal, and long-term reversal. We report second-stage risk-price estimates (in percent per year), GMM-corrected t-statistics, R^2, and the mean absolute pricing error (MAPE). The scale-wise exposures are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. The sample period is 1965:Q1 to 2011:Q4.

		λ_0	$\lambda^{(1:4)}$	$\lambda^{(>4)}$	R^2 [MAPE]
		Panel A: 25 Size- and book-to-market-sorted portfolios			
CG	$j > 4$	-0.21		2.04	0.480
		(-0.05)		(2.65)	[1.649]
	$j = 1:4$ & $j > 4$	-0.46	0.09	2.05	0.458
		(-0.15)	(0.10)	(3.73)	[1.647]
CRAG	$j > 4$	0.17		2.30	0.622
		(0.04)		(3.34)	[1.417]
	$j = 1:4$ & $j > 4$	-1.13	0.50	2.27	0.637
		(-0.38)	(0.54)	(3.54)	[1.393]
		Panel B: The market, 5 book-to-market portfolios, and 5 bond portfolios			
CG	$j > 4$	0.55		2.54	0.815
		(0.42)		(1.64)	[0.836]
	$j = 1:4$ & $j > 4$	-0.53	-1.75	4.19	0.850
		(-0.54)	(-1.30)	(3.11)	[0.753]
CRAG	$j > 4$	-0.09		2.70	0.932
		(-0.06)		(1.94)	[0.528]
	$j = 1:4$ & $j > 4$	0.09	0.19	2.53	0.925
		(0.09)	(0.14)	(3.10)	[0.536]
		Panel C: 30 Characteristics-sorted portfolios			
CG	$j > 4$	-3.83		1.68	0.655
		(-0.68)		(2.44)	[0.944]
	$j = 1:4$ & $j > 4$	-2.98	-0.28	1.73	0.661
		(-1.11)	(-0.53)	(4.76)	[0.894]
CRAG	$j > 4$	-3.66		1.75	0.714
		(-0.85)		(3.31)	[0.860]
	$j = 1:4$ & $j > 4$	-3.84	0.04	1.74	0.703
		(-1.42)	(0.09)	(4.70)	[0.861]

Table IA.7: **Low frequency consumption risk versus unfiltered consumption of Kroencke (2014)**

This table runs a horse race of our measure of consumption risk, i.e., exposure to low frequency variation at scale $j > 4$ in standard NIPA, per capita, non-durables and services consumption growth ($\beta_{CG}^{(>4)}$, estimated using quarterly excess simple returns as in Table IA.6) versus covariance with the unfiltered consumption measure of Kroencke (2014) ($Cov(UFCG_{t+1}, r_{t+1}^{e,i})$, estimated using annual excess log returns as in his paper). We use the series that works best in his empirical test, i.e, quarter four to quarter four non-durables (ex. services) consumption growth adjusted for the effects of time aggregation and filtering. We run this horse race for the usual three sets of portfolios in Panels A to C. We report point estimates from the second-stage cross-sectional regression of average quarterly excess simple returns on the risk exposures as well as Fama and MacBeth (1973) t-statistics, R^2, and the mean absolute pricing error (MAPE). $\beta_{CG}^{(>4)}$ is normalized such that the point estimate, $\lambda^{>4}$, can be interpreted as the risk premium in percent per year per cross-sectional standard deviation in exposure. In contrast, $Cov(UFCG_{t+1}, r_{t+1}^{e,i})$ is not normalized, such that the point estimate, γ_{UFCG}, can be interpreted as an estimate of the coefficient of relative risk aversion in the consumption-CAPM. The sample period is 1965:Q1 to 2011:Q4.

	λ_0	$\lambda^{>4}$	γ_{UFCG}	R^2 [MAPE]
Panel A: 25 Size- and book-to-market-sorted portfolios				
$Cov(UFCG_{t+1}, r_{t+1}^{e,i})$	-0.70		25.69	0.320
	(-0.21)		(2.21)	[1.733]
$\beta_{CG}^{(>4)}$ & $Cov(UFCG_{t+1}, r_{t+1}^{e,i})$	-2.72	1.59	12.26	0.516
	(-0.80)	(2.25)	(0.85)	[1.542]
Panel B: The market, 5 book-to-market portfolios, and 5 bond portfolios				
$Cov(UFCG_{t+1}, r_{t+1}^{e,i})$	2.20		14.64	0.852
	(2.76)		(1.94)	[0.829]
$\beta_{CG}^{(>4)}$ & $Cov(UFCG_{t+1}, r_{t+1}^{e,i})$	1.99	0.31	12.95	0.834
	(2.88)	(0.22)	(1.34)	[0.818]
Panel C: 30 Characteristics-sorted portfolios				
$Cov(UFCG_{t+1}, r_{t+1}^{e,i})$	2.20		18.34	0.074
	(0.76)		(1.52)	[1.475]
$\beta_{CG}^{(>4)}$ & $Cov(UFCG_{t+1}, r_{t+1}^{e,i})$	-1.36	1.95	-12.70	0.679
	(-0.46)	(4.66)	(-0.86)	[0.907]

Table IA.8: **Bryzgalova's (2015) Pen-FM estimates for high and low frequency IPG risk** This table presents the price of risk estimates from the penalized cross-sectional regression (Pen-FM) procedure developed in Bryzgalova (2015). The penalty ensures that the price of risk of weak factors is shrunk towards zero. We focus on the same set of portfolios as in Table 5 of the paper, which table is also relevant for benchmarking the Pen-FM estimates of the low ($j > 4$) and high ($j = 1:4$) frequency price of growth risk. We present the Pen-FM estimates as well as the standard error (in brackets) and p-value from 2500 bootstrap replications (the p-value (in parentheses) equals the fraction of bootstrap replications in which $\lambda^{(>4)} \leq 0$ or $\lambda^{(1:4)} \leq 0$). For the Pen-FM estimation and bootstrap, we use tuning parameters that are consistent with Bryzgalova (2015, Equation 9), setting d equal to four and η equal to the square root of the average variance of the first-stage (components of) portfolio returns. To accommodate our component-wise estimation procedure in the bootstrap, we (pairwise) re-sample the components of returns and components of IPG. The adjusted R^2 follows from a regression of average returns on betas, which are standardized to have standard deviation equal to one in the data and each bootstrap replication.

	25 Portfolios		11 Portfolios		30 Portfolios	
	$j > 4$	$j = 1:4$	$j > 4$	$j = 1:4$	$j > 4$	$j = 1:4$
λ_0	-0.791	8.723	-0.759	4.453	-3.132	8.630
$\lambda^{(>4)}$ or $\lambda^{(1:4)}$	2.337	0.000	2.614	0.026	1.619	0.000
St. err. bootstrap	[0.787]	[0.476]	[1.384]	[0.975]	[0.478]	[0.298]
p-val bootstrap	(0.092)	(0.688)	(0.046)	(0.527)	(0.079)	(0.673)
Adj. R^2	0.692	-0.043	0.906	-0.092	0.642	-0.036

Table IA.9: **Alternative measures of volatility: Cross-sectional regressions for individual stocks**

The table is the equivalent of Table 8 and reports second-stage cross-sectional regressions of quarterly excess returns of individual stocks on lagged volatility risk loadings and characteristics, where volatility risk is measured using either (i) non-durables and services consumption growth (CG) or (ii) a composite measure of macroeconomic growth (CRAG), defined as the first principal component extracted from the growth rates of industrial production, consumption, employment and unemployment. The volatility risk loadings are first-stage betas estimated using a five-year rolling window component-wise time-series regression of the j-th component of excess returns on the innovation in the components of conditional CG volatility ($u^{(j)}_{CGVOL,t}$, Panel A), the innovation in the components of the out-of-sample CG volatility series ($u^{(j)}_{CGVOL-OOS,t}$, Panel B), or, the innovation in the components of conditional CRAG volatility ($u^{(j)}_{CRAGVOL,t}$ (Panel C). CGVOL and CRAGVOL are estimated using an AR(1)-GARCH(1,1) model over the full sample, whereas CGVOL-OOS is estimated in each quarter t using only historical data over the expanding window starting from 1947Q2. We report time-series averages of the point estimates from the second stage, with Fama and MacBeth (1973) t-statistics presented underneath in parenthesis, as well as the cross-sectional R^2. The scale-wise exposures to volatility risk are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. The sample period is 1965:Q1 to 2011:Q4.

	λ_0	$\lambda_{vol}^{(1:4)}$	$\lambda_{vol}^{(>4)}$	γ_{SIZE}	γ_{BM}	R^2
Panel A: Scale-wise consumption volatility risk						
$j = 1:4$ & $j > 4$	8.08	-0.32	-2.42			0.019
	(2.87)	(-0.43)	(-3.27)			
$SIZE^i_t$, BM^i_t	8.49	-0.64	-1.54	-2.46	1.74	0.049
	(2.94)	(-1.02)	(-2.49)	(-2.34)	(2.78)	
Panel B: Out-of-sample consumption volatility risk						
$j = 1:4$ & $j > 4$	8.10	-0.05	-2.46			0.019
	(2.93)	(-0.06)	(-3.57)			
$SIZE^i_t$, BM^i_t	8.75	-0.48	-1.64	-2.54	1.77	0.048
	(3.07)	(-0.72)	(-2.90)	(-2.44)	(2.84)	
Panel C: Scale-wise composite real activity volatility risk						
$j = 1:4$ & $j > 4$	8.91	0.00	-2.39			0.020
	(3.17)	(0.01)	(-3.45)			
$SIZE^i_t$, BM^i_t	9.55	-0.24	-1.77	-2.84	1.55	0.049
	(3.31)	(-0.43)	(-3.26)	(-2.66)	(2.41)	

Table IA.10: **Alternative measures of volatility: Cross-sectional regressions for portfolios** This table presents portfolio-level cross-sectional regressions for macroeconomic volatility risk as in Table 10 of the paper, but substitutes the conditional volatility of consumption (CVOL) or the composite measure of real activity (CRAVOL) for IPVOL as our measure of macroeconomic volatility. The table reports risk-price estimates (in percent per year) from cross-sectional regressions of portfolio-level average excess returns on full sample volatility risk loadings with respect to innovations in the components of conditional CG and CRAG volatility, which are estimated using an AR(1)-GARCH(1,1) model for CG and CRAG over the full sample ($u^{(j)}_{CVOL,t}$ and $u^{(j)}_{CRAVOL,t}$). We focus on $j = 1:4$ and $j > 4$ and three sets of portfolios: Fama and French's (1993) 25 size and book-to-market portfolios; 11 stock and bond portfolios as in Koijen et al. (2013) (the market portfolio, five book-to-market portfolios and five constant maturity treasury bond portfolios); and, 30 quintile portfolios sorted on six different characteristics: size, book-to-market, operating profitability, investment, short-term reversal and long-term reversal. We report second-stage risk-price estimates, GMM-corrected t-statistics, R^2, and the mean absolute pricing error (MAPE). The scale-wise exposures to macroeconomic volatility risk are normalized, such that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. The sample period is 1965:Q1 to 2011:Q4.

		λ_0	$\lambda_{vol}^{(1:4)}$	$\lambda_{vol}^{(>4)}$	R^2 [MAPE]
Panel A: 25 Size- and book-to-market-sorted portfolios					
CVOL	$j > 4$	2.93		-2.29	0.613
		(0.86)		(-3.22)	[1.354]
	$j = 1:4$ & $j > 4$	2.58	0.20	-2.31	0.601
		(0.98)	(0.22)	(-3.51)	[1.347]
CRAVOL	$j > 4$	3.11		-2.28	0.608
		(0.79)		(-3.01)	[1.428]
	$j = 1:4$ & $j > 4$	-0.26	1.29	-3.06	0.726
		(-0.09)	(1.16)	(-3.53)	[1.072]
Panel B: The market, 5 book-to-market portfolios, and 5 bond portfolios					
CVOL	$j > 4$	1.59		-2.57	0.835
		(1.72)		(-2.17)	[0.729]
	$j = 1:4$ & $j > 4$	1.08	0.90	-2.34	0.938
		(1.23)	(0.98)	(-2.53)	[0.478]
CRAVOL	$j > 4$	0.38		-2.58	0.841
		(0.32)		(-2.17)	[0.764]
	$j = 1:4$ & $j > 4$	-0.02	0.85	-2.55	0.937
		(-0.02)	(0.86)	(-2.56)	[0.467]
Panel C: 30 Characteristics-sorted portfolios					
CVOL	$j > 4$	1.00		-1.72	0.691
		(0.26)		(-3.88)	[0.789]
	$j = 1:4$ & $j > 4$	0.34	0.14	-1.78	0.684
		(0.14)	(0.31)	(-5.02)	[0.788]
CRAVOL	$j > 4$	2.04		-1.39	0.439
		(0.45)		(-3.15)	[0.998]
	$j = 1:4$ & $j > 4$	-2.46	0.94	-1.96	0.564
		(-0.87)	(1.99)	(-5.17)	[0.869]

Table IA.11: **Growth or volatility risk? Alternative measures of macroeconomic activity** This table is analogous to Table 11 and reports risk premium estimates from cross-sectional regressions of excess returns on estimated growth and volatility risk loadings, where growth and volatility are measured using consumption growth (CG, Panel A) or the composite measure of real activity (CRAG, Panel B). Risk loadings for this two-factor model are obtained from two separate scale-wise time-series regressions of the long-term component of returns on (i) the long-term component of growth, i.e., either $\beta^{(>4)}_{i,CG,t}$ or $\beta^{(>4)}_{i,CRAG,t}$, and (ii) the long-term component of volatility, i.e., either $\delta^{(>4)}_{i,CVOL,t}$ or $\delta^{(>4)}_{i,CRAVOL,t}$. We consider both stock-level tests, where the loadings are estimated over a five-year historical rolling window, and portfolio-level tests, where the loadings are estimated over the full sample. We consider three sets of portfolios: Fama and French's (1993) 25 size and book-to-market portfolios (25P); 11 stock and bond portfolios as in Koijen et al. (2013) (11P, i.e., the market portfolio, five book-to-market portfolios and five constant maturity treasury bond portfolios); and, 30 quintile portfolios sorted on six different characteristics (30P): size, book-to-market, operating profitability, investment, short-term reversal and long-term reversal. For the stock-level test, we report time-series averages of the second-stage risk-price estimates, with Fama and MacBeth (1973) t-statistics presented underneath in parenthesis, as well as the cross-sectional R^2. For the portfolio-level tests, we report second-stage risk-price estimates, GMM-corrected t-statistics (in parenthesis), R^2, and the mean absolute pricing error (MAPE). The scale-wise exposures to macroeconomic risk are normalized so that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation in exposure. The sample period is 1965:Q1 to 2011:Q4.

Panel A: Consumption growth versus volatility at scale $j > 4$

$$R^{e,i}_{t+1} = \lambda_{0,t} + \lambda^{(>4)}_{growth,t}\beta^{(>4)}_{i,t} + \lambda^{(>4)}_{vol,t}\delta^{(>4)}_{i,t} + \alpha_{i,t+1}$$

		λ_0	$\lambda^{(>4)}_{growth}$	$\lambda^{(>4)}_{vol}$	R^2 [MAPE]
Stocks		8.70	0.34	-3.10	0.021
		(2.98)	(0.20)	(-1.60)	
Portfolios	25P	1.66	0.55	-1.84	0.609
		(0.48)	(1.65)	(-2.71)	[1.310]
	11P	0.75	1.33	-1.48	0.912
		(0.69)	(0.89)	(-1.82)	[0.527]
	30P	-2.56	0.88	-1.06	0.762
		(-0.83)	(1.81)	(-2.25)	[0.764]

Panel B: Composite real activity growth versus volatility at scale $j > 4$

$$R^{e,i}_{t+1} = \lambda_{0,t} + \lambda^{(>4)}_{growth,t}\beta^{(>4)}_{i,CRAG,t} + \lambda^{(>4)}_{vol,t}\beta^{(>4)}_{i,CRAVOL,t} + \alpha_{i,t+1}$$

		λ_0	$\lambda^{(>4)}_{growth}$	$\lambda^{(>4)}_{vol}$	R^2 [MAPE]
Stocks		8.88	0.13	-2.38	0.019
		(3.05)	(0.09)	(-1.52)	
Portfolios	25P	1.18	1.36	-1.01	0.622
		(0.41)	(1.44)	(-0.83)	[1.358]
	11P	-0.10	2.24	-0.50	0.929
		(-0.09)	(0.85)	(-0.27)	[0.521]
	30P	-3.56	1.59	-0.21	0.708
		(-1.03)	(3.10)	(-0.37)	[0.864]