Firm Characteristics, Consumption Risk, and Firm-Level Risk Exposures*

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Abstract

Firm-level risk exposures and costs of equity are notoriously difficult to estimate. Using a novel approach mapping consumption risk exposures to firm characteristics, we combine the traditional portfolio-level approach to testing asset pricing models with firm-level information to measure firm-level risk exposures. First, at the portfolio level, we investigate the empirical performance of a simple two-factor consumption-based asset pricing model for the cross-section of equity returns. The priced factors in the model are innovations in the growth and volatility of aggregate consumption. Our empirical results show that this model can explain 66% of the cross-sectional variation in returns on a menu of 55 portfolios spanning size, value, momentum, asset growth, stock issuance, and accruals. Second, we use the estimated model to map point-in-time firm characteristics to consumption risk exposures. Through this measurement procedure, we uncover sizeable cross-sectional and time-series variation in firm consumption risk exposures. We verify that sorting on these *ex ante* consumption risk exposures produces portfolios with consistent *ex post* risk exposures and predicts cross-sectional variation in future firm equity returns.

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1 Introduction

In the past fifteen years, consumption-based asset pricing has experienced something of a renaissance. While hope had waned for the consumption-based paradigm in the wake of empirical failures such as the equity premium puzzle of Mehra and Prescott (1985), recent theoretical advances in the field, including the habit formation model of Campbell and Cochrane (1999) and the long run risk model of Bansal and Yaron (2004) have provided new mechanisms for connecting financial asset prices to real economic quantities such as consumption growth. Moreover, recent empirical evidence, especially regarding consumption-based models' ability to capture cross-sectional variation in returns, has resulted in a new interest in understanding the links between consumption growth and asset prices.[1]

One might expect, given the more recent empirical success of consumption-based pricing models in explaining cross-sectional variation in returns, that such models would be used widely in finance for return benchmarking and risk measurement. However, to our knowledge, this does not seem to be the case. Rather, end users of asset pricing models instead continue to rely on the Capital Asset Pricing Model (CAPM) or factor models such as Fama and French (1993, 2014) or Carhart (1997).[2] In our view, this is somewhat surprising given the empirical failures of the CAPM, as documented in Fama and French (1992), and the lack of a direct link of *ad hoc* statistical factor models to economic theory. We conjecture that among the reasons that consumption-based models have not gained greater traction for risk adjustment is the difficulty in measuring asset return exposures to low-frequencyconsumption risk. This difficulty is particularly pronounced at the disaggregated level, especially at the level of the firm. It is this measurement challenge that we address in this paper.

Measurement of disaggregated risk exposures is notoriously difficult, as has been noted by Fama and French (1997), who attempt to measure industry risk exposures to the Fama and French (1993) factors. The authors note that the ratio of industry-specific variance to systematic variance is high, resulting in imprecise measures of risk exposure. They also speculate that industry risk exposures are likely to be time-varying, exacerbating the measurement problem. The authors conclude that if

[1] There are many examples of empirical studies that find a link between consumption and cross-sectional variation in average returns. Parker and Julliard (2005) find that covariance of asset returns with future consumption growth has explanatory power for the cross section of firms. Bansal, Dittmar, and Lundblad (2005) show that covariation of cash flows with a long-run moving average of consumption growth generates cross-sectional risk premia. Yogo (2006) derives a model with nonseparable consumption of nondurable goods, and shows that growth in durable goods consumption explains cross-sectional variation in returns. Jagannathan and Wang (2007) find that measuring consumption growth as the growth in year-on-year fourth quarter consumption explains a substantial portion of cross-sectional variation in returns. Finally, Savov (2011) uses garbage as a measure of consumption and finds cross-sectional variation in returns associated with garbage production.

[2] Hou, Xue, and Zhang (2014) explore the performance of a four-factor model based in the q-theory of investment. The model is motivated by the implications of the theory for the components of the return on an equity claim. However, there is no direct link to the source of priced risk in the stochastic discount factor.

these problems are present in industry portfolios, they are likely to be even more severe at further disaggregated levels, such as that of individual firms. These issues are even more likely to affect measurement of exposure to consumption risk. Because consumption data is observed only at low frequencies, and because recessions are central to macroeconomic risk exposure but infrequent, it is probable that direct estimates of firm return exposure to consumption risk will be difficult to obtain.

In this paper, we propose a methodology to address these problems. Specifically, our method follows the suggestion of production-based asset pricing models such as Zhang (2005) that imply a link between firm characteristics and risk exposures. These models suggest that risk exposures are related to characteristics through the composition of the return to firms' optimal investment. These risk exposures, in turn, should relate to the covariance of a firm's returns with some source of aggregate priced risk. We posit a model in which the priced risks are innovations to the level and volatility of consumption growth, and test the model on a set of portfolios formed on six firm characteristics: asset growth, book-to-market ratio, market capitalization, past 12-month return, stock issuance, and total accruals. Our empirical results show that low-frequency covariation of equity returns and consumption growth innovations explains nearly two-thirds of the cross-sectional variation in average returns on these portfolios.

Our empirical results suggest a link between expected returns and consumption risk exposures. In turn, production-based pricing models suggest a link between risk exposures and characteristics. We show that consumption risk exposures are related to characteristics at the portfolio level, and use the portfolio level relation to infer firm-level risk exposures. In order to assess whether the procedure generates portfolios correctly sorted on consumption risk exposures, we form portfolios using only information available at the time of the portfolio formation to generate quintile portfolios on the basis of *ex ante* exposure to consumption risk. We find that the resulting portfolios have *ex post* exposures to consumption risk of roughly the same magnitude as the *ex ante* exposures. Further, our equally-weighted portfolio returns generate an average return differential of 91 basis points per month between the fifth and first quintile of *ex ante* beta. This return premium is robust to adjustment for the risk factors in Fama and French (2014) and Hou, Xue, and Zhang (2014).

Finally, we approach the estimation of the cost of capital for different industry portfolios, similar to the exercise in Fama and French (1997). Industry portfolios are aggregated, thereby enjoying the usual portfolio diversification effects (in comparison to firm-level analysis), but they also likely exhibit significant cross-sectional and time-series variation in industry characteristics along with temporal variation in consumption risk exposures. While we view our contribution as providing a methodology to evaluate consumption risk exposures at the most disaggregated levels, industry portfolios do provide a natural laboratory in which to evaluate our methodology. We find that time-variation in risk exposures is important for understanding the cost of industry capital;

while regressions of mean returns on average *ex ante* betas generate no statistically significant risk premium, Fama and MacBeth (1973) regressions of returns on risk consumption expsoures suggest a positive and statistically significant price of consumption beta risk. We also show that the time-series variation in industry risk exposures do suggest countercyclical risk premia.

We view the main contribution of the paper as proposing a method for linking consumption-based asset pricing to the measurement of firm- and industry-level risk exposures. As such, the paper builds on a large literature of recent theoretical and empirical advances. Our pricing model can be viewed as a reduced-form version of the model proposed in Bansal and Yaron (2004). The empirical framework for estimating consumption risk exposures draws on empirical evidence in Parker and Julliard (2005), Bansal, Dittmar, and Lundblad (2005), Hansen, Heaton, and Li (2008), and Bansal, Dittmar, and Kiku (2009) that suggests that low frequency covariation in returns and consumption growth are important for understanding cross-sectional variation in average returns.

Our work also briefly touches on literature that suggests that aggregate volatility is important in asset pricing, including Ang, Hodrick, Xing, and Zhang (2006), Boguth and Kuehn (2013), Bansal, Kiku, Shaliastovich, and Yaron (2013), and Campbell, Giglio, Polk, and Turley (2013). Ultimately, we find that volatility in consumption growth generates relatively little improvement in model fit. However, this result may be a function of our choice for modeling volatility or our choice of test assets. Our methodology applies in principle to measurement of volatility risk as well, and one could construct firm-level exposures to aggregate volatility risk in addition to the measures of consumption growth risk presented in this paper.

The remainder of the paper is organized as follows. In Section 2, we discuss the estimation of consumption innovation risks and the theoretical framework in which these risks are priced. We estimate risk exposures and analyze cross-sectional regressions of portfolio mean returns on risk measures in Section 3. Section 4 presents an analysis of utilizing portfolio characteristics and risk exposures to capture firm-level risk exposures. An application to industry cost of capital is presented in Section 5. We make concluding remarks in Section 6.

2 Theoretical Framework

2.1 Relating Risk Exposures and Firm Characteristics

An early suggestion that characteristics might proxy for risk measures is provided by Fama and French (1992). The authors argue that size and book-to-market capture cross-sectional variation in average returns because they proxy for exposures to risks other than that embodied in the market portfolio. This intuition is formalized in the context of an investment-based asset pricing model in Zhang (2005). He shows that when risk premia are countercyclical, and costs of adjustment to investment are asymmetric, assets in place can be riskier than growth options during economic downturns. This risk leads to a larger unconditional risk premium for firms with a higher proportion of assets in place. High book-to-market firms are likely to have a greater proportion of capital invested in assets in place than growth options, suggesting that their returns are riskier. As a result, high book-to-market firms earn a higher risk premium than low book-to-market firms, and book-to-market represents a proxy for a firm's exposure to risk.

This point is made more explicit in Lin and Zhang (2013), who argue forcefully that characteristics and risk factor covariances represent two sides of the same coin. For example, the authors show that in a simple production-based model, the risk premium on an equity can be written as

$$\begin{aligned} E_t\left[r_{i,t+1}^S\right] - r_{f,t} = \beta_i^M \lambda_M = r_{i,t+1}^I &= \frac{E_t\left[\Pi_{i,t+1}\right]}{1 + a\left(I_{i,t}/K_{i,t}\right)}, \\ \beta_i^M &= \left[\frac{E_t\left[\Pi_{i,t+1}\right]}{1 + a\left(I_{i,t}/K_{i,t}\right)} - r_f\right]/\lambda_M, \end{aligned} \tag{1}$$

where $r_{i,t}^S$ is the return on firm i's equity, $r_{f,t}$ is the risk-free rate, β_i^M is the exposure of the firm's equity return to a stochastic discount factor M_{t+1}, λ_M is the price of stochastic discount factor risk, $r_{i,t+1}^I$ is the return on the firm's investment, $\Pi_{i,t}$ is a profit function, $I_{i,t}$ is investment, $K_{i,t}$ is capital, and a is an adjustment cost parameter. This relation makes it clear that the firm's risk exposure can be expressed as functions of profitability and investment intensity, as captured by the investment-to-capital ratio. In equilibrium, Lin and Zhang (2013) note that the denominator $1 + a\left(I_{i,1}/K_{i,1}\right)$ will be the market-to-book ratio, establishing the link between firm characteristics and risk exposures.

Investment-based asset pricing has been linked to a number of firm characteristics in addition to the book-to-market ratio, including stock issues (Lyandres, Sun, and Zhang (2008) and Li, Livdan, and Zhang (2009)), accruals (Wu, Zhang, and Zhang (2010)), and momentum (Liu and Zhang (2014)). These characteristics can be linked to the return on investment and return on equity by introducing more complicated adjustment costs, corporate taxes, and debt. As an example, Liu, Whited, and Zhang (2009) consider an investment-based model with leverage and taxes that breaks the perfect correlation between the return to equity and investment. In this framework, characteristics are related to a firm's investment return and the relation between the investment return and the equity return. As a result, the characteristics are linked to equity's exposure to risks in the stochastic discount factor.

We implement this idea by assuming that the relation between an asset's risk exposure and the set of characteristics important for determining the return on investment and its relation to the return on equity can be captured by projecting the risk exposure onto the set of characteristics.

Specifically, we assume that

$$\beta_{i,k,t} = f(\mathbf{x}_{i,t}, \boldsymbol{\delta}_t) + \xi_{i,k,t}, \tag{2}$$

where $\beta_{i,k,t}$ is the time t exposure of asset i's return to factor k, $\mathbf{x}_{i,t}$ is a set of relevant characteristics, and $\boldsymbol{\delta}_t$ is a set of potentially time-varying coefficients. In principle, we would prefer to map the return on investment directly into the risk premium implied by a candidate stochastic discount factor. However, it is unclear whether the error resulting from this projection or mis-specification of the relation between the return on investment and the characteristics would result in larger mis-measurement of the relation between risk exposures and characteristics. Therefore, we utilize this projection as a reasonable first approximation implied by relations such as equation (1), which link equity risk premia to the return on investment.

2.2 Expected Returns and Consumption Moments

At the center of the production-based asset pricing framework is the notion that firm's invest optimally. In the context of the model, this means that they maximize firm value, defined as the discounted sum of the firm's expected future dividends. The model assumes that the stochastic discount factor (SDF) is determined by consumers in the economy, but does not directly specify this SDF. The risk exposure in equation (1) is the covariance of the return on a firm's return on equity with this SDF, and as such the SDF is central to measuring a firm's expected return.

Our particular interest in this paper is in models of the stochastic discount factor that are functions of risks in aggregate consumption growth. In particular, we have in mind a model in the vein of the canonical Lucas (1978) asset pricing model, which Lucas (1978), which states that an asset's price is determined by its conditional covariance with a representative agent's intertemporal marginal rate of substitution (IMRS),

$$E_t\left[\exp\left(m_{t+1} + r_{i,t+1}\right)\right] = 1 \tag{3}$$

where m_{t+1} is the log IMRS or stochastic discount factor, $r_{i,t+1}$ is the log gross return on a risky asset i, and the price of the asset is normalized to unity. Under the further assumption of conditional joint lognormality of the IMRS and the asset return, we can rewrite equation (3) as

$$E_t\left[r_{i,t+1}\right] + \frac{1}{2}Var_t\left(r_{i,t+1}\right) = -E_t\left[m_{t+1}\right] - \frac{1}{2}Var_t\left(m_{t+1}\right) - Cov_t\left(m_{t+1}, r_{i,t+1}\right). \tag{4}$$

Equation (4) emphasizes the fact that expected returns on assets in the cross-section are related to the covariation of innovations in the IMRS and the asset payoff.

A large number of formulations for investors' utility yield a form for the IMRS that is log-linear in the moments of consumption growth. Two cases are of particular interest for our study. The first is power utility, in which the log pricing kernel

$$m_{t+1} = \ln \delta - \gamma \Delta c_{t+1},$$

with γ representing the agent's relative risk aversion, Δc_{t+1} representing log growth in consumption, and δ reflecting the agent's time preference. The second is Epstein and Zin (1989) utility, in which the log pricing kernel is represented as

$$m_{t+1} = \theta \ln \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1)\, r_{c,t+1}.$$

In this expression, ψ represents the intertemporal elasticity of substitution, which is separable from risk aversion, γ, $\theta = (1-\gamma)/(1-1/\psi)$, and $r_{c,t+1}$ is the log payoff of an asset that pays aggregate consumption as its dividend. Power utility is a special case where $\gamma = 1/\psi$ and, consequently, $\theta = 1$.

Bansal and Yaron (2004) suggest parameterizing the log return on the consumption claim as a linear function of the state variables of the economy and consumption growth,

$$r_{c,t+1} \approx \kappa_0 + \kappa_1 \mu_{t+1} + \kappa_2 \sigma^2_{c,t+1} + \Delta c_{t+1}, \tag{5}$$

where μ_{t+1} is the conditional expectation of future consumption growth and $\sigma^2_{c,t+1}$ is its conditional variance. We further assume that

$$\begin{aligned} \Delta c_{t+1} &= \mu_t + \sigma_t \eta_{t+1} \\ \mu_{t+1} &= \mu_c + \rho \mu_t + \varphi \sigma_t \eta_{t+1} \\ \sigma^2_{t+1} &= E_t\left[\sigma^2_{t+1}\right] + \sigma_w w_{t+1}, \end{aligned}$$

where η_{t+1} and w_{t+1} are standard normal i.i.d. shocks. These dynamics are similar to those explored in Bansal and Yaron (2004), but we assume that the shock to consumption and its conditional mean are the same. As a result, consumption growth is an ARMA(1,1) dynamic process with time-varying volatility.

Under the assumption of log-linearity of the return on the consumption claim in the two state variables, the risk premium on an asset can be determined from equation (4) by

$$\begin{aligned} E\left[r_{i,t+1} - r_{f,t}\right] &= -Cov\left(m_{t+1} - E_t\left[m_{t+1}\right], r_{i,t+1} - E_t\left[r_{i,t+1}\right]\right) - \frac{1}{2} Var\left(r_{i,t+1}\right) \\ &= \pi_1 Cov\left(\sigma_t \eta_{t+1}, \eta_{i,t+1}\right) + \pi_2 Cov\left(w_{t+1}, \eta_{i,t+1}\right) - \frac{1}{2} Var\left(r_{i,t+1}\right), \qquad (6) \end{aligned}$$

where

$$\pi_1 = \frac{\theta}{\psi} - (\theta - 1)(\kappa_1 \varphi - 1)$$
$$\pi_2 = \kappa_2 (\theta - 1),$$

and $\eta_{i,t+1} = r_{i,t+1} - E_t[r_{i,t+1}]$, the shock to the asset return. This expression indicates that investors expect risk premia to compensate for shocks to first moment of consumption risk, η_{t+1}, and second moment of consumption risk w_{t+1}. Bansal and Yaron (2000) note that under power utility, $\theta = 1$, and therefore second moment risk will not be compensated in returns.

Converting back to arithmetic returns, the risk premium (6) can be expressed as

$$E[R_{i,t+1} - R_{f,t}] = \lambda_1 \beta_{i,\eta} + \lambda_2 \beta_{i,w}, \tag{7}$$

where $\beta_{i,\eta} = Cov(r_{i,t+1}, \eta_{t+1}) / Var(\eta_{t+1})$ and $\beta_{i,w} = Cov(r_{i,t+1}, w_{t+1}) / Var(w_{t+1})$ are coefficients of regressing returns on the innovations η_{t+1} and w_{t+1}. This expression suggests that cross-sectional variation in risk premia will be determined by assets' return exposures to shocks to the first and second moments of consumption growth. Under power utility, $\lambda_2 = 0$ and only the conditional covariance of consumption growth levels with innovations in asset returns will bear risk premia. Under the further assumption of i.i.d. consumption growth, $\beta_{i,\eta}$ is simply captured by the covariance of returns with consumption growth.

3 Consumption Risk Premia in Average Returns

3.1 Testing Portfolios

A wide variety of firm-specific characteristics have been used as instruments to guide portfolio formation. Fama and French (1992) suggest that the cross-section of returns can be summarized by size and book-to-market, and advocate the use of portfolios sorted on these two variables in Fama and French (1993). The use of these portfolios in asset pricing tests, however, has come under recent criticism by Lewellen, Nagel, and Shanken (2010) due to the ease of fitting a model to their two-factor structure. Harvey, Liu, and Zhu (2014) catalog 316 variables that have been found to have significant power to forecast cross-sectional variation in returns, and Green, Hand, and Zhang (2014) report over 330, and find 24 to be reliably statistically significant. Lewellen (2014) considers a set of 15 predictors, and finds that while 10 have significant t-statistics in Fama and MacBeth (1973) regressions, most of the variation in expected returns can be traced to log size, book-to-market, and past 12-month return. These papers suggest that the answer of which characteristics are relevant for testing asset pricing models remains unclear.

We utilize a set of six characteristics to form portfolios: These variables are growth in assets (AG), log book-to-market ratio (BM), log market capitalization (MV), past 12-month returns (P12), stock issues (SI), and total accruals (TA). These variables are found to have statistically significant t-statistics in Fama and MacBeth (1973) regressions, regardless of whether the tests are conducted on all stocks, all stocks but micro-caps, or only large stocks by Lewellen (2014).[3] We form portfolios based on deciles of all of the characteristics except stock issuance. Cross-sectional dispersion in stock issuance is not wide, with a large mass of firms neither issuing nor repurchasing stock. Consequently, we form portfolios on quintiles of stock issuance. We opt to use univariate sorts rather than intersections because of the difficulty in forming well-diversified portfolios on the basis of the intersection of three or more characteristics. As noted by Fama and French (2014), it is difficult to generate well-diversified portfolios and fully populated intersections when using more than four characteristics and characteristic quantile cutoffs finer than the 50th percentile. Details of the calculation of the characteristics are provided in the appendix. Porfolios are value-weighted with returns sampled at the quarterly frequency and converted to real using the personal consumption expenditure (PCE) deflator from the Bureau of Economic Analysis. Data are sampled from the 3rd quarter of 1953 through the fourth quarter of 2013.

Summary statistics for the portfolio returns are presented in Table 1. Mean returns exhibit patterns that are now familiar to readers of the empirical asset pricing literature; average returns increase in the book-to-market ratio and past 12-month return, and decrease in market value, asset growth, total accruals, and stock issues. None of the average returns are perfectly monotonic in their characteristic deciles, but some characteristics appear to generate more nearly monotonic patterns than others. In particular, past 12-month returns appear to generate very nearly monotonic patterns in average returns, with only one deviation in the deciles; similarly, stock issuance quintiles deviate in monotonicity only in the middle quintile. The data suggest quite a large dispersion in average returns as well; the highest average real return is on the tenth decile past 12-month return portfolio of 4.21%, and the lowest is on the first decile past 12-month return portfolio of -0.71%. The remaining sorts generate differences in average quarterly returns returns of 1.08% for the difference in the bottom and top stock issuance quintile to 1.69% for the difference in the bottom and top market value decile.

[3] Lewellen (2014) finds that in addition to the six characteristics that we consider, profitability has robust predictive power for returns. Further, a profitability factor features prominently in both the five-factor model proposed by Fama and French (2014) and the four-factor q-theory model of Hou, Xue, and Zhang (2014). Including profitability as a characteristic for forming portfolios results in a deterioration of the cross-sectional fit of the model, which in turn adversely impacts fitting firm-level risk exposures. In an online appendix, we replicate all of the results in this paper including a set of profitability-sorted portfolios.

3.2 Estimating Risk Exposures

The model presented in Section 2 suggests that the priced sources of risk are innovations in the mean and the volatility of consumption growth, which in turn requires specification of a time series model for the conditional moments. In typical estimates of the autocorrelation of consumption growth, empirical evidence finds positive and statistically significant autocorrelation coefficients (see, for example, Piazzesi (2001)). However, the conclusions drawn from a statistically significant autocorrelation coefficient are a subject of debate. Working (1960) shows that time aggregated i.i.d. shocks can exhibit statistically significant autocorrelation and, as a result, it is possible that the autocorrelation estimated in observed consumption growth is due to time aggregation rather than actual dynamics of the underlying process. Opposing viewpoints on this issue have recently been aired in Beeler and Campbell (2012) and Bansal, Kiku, and Yaron (2012).

Our approach is to proceed as simply as possible, and sidestep controversy over the dynamics of consumption growth. We assume a constant mean of consumption growth and simply use demeaned consumption growth as the innovation in the level of consumption growth, η_{t+1}. The possibility of conditional volatility in consumption growth is perhaps less controversial. We again approach modeling this conditional volatility quite simply assuming that innovations to volatility can be captured through an AR(1) of model of squared level innovations,

$$\eta_{t+1}^2 = \nu_0 + \nu_1 \eta_t^2 + w_{t+1}.$$

Our results are robust to using more complicated models for the dynamics of the volatility of consumption growth, such as GARCH (1,1) or EGARCH (1,1).

An additional issue in estimating risk exposures is the contribution of low-frequency movements in consumption growth to its riskiness. Bansal, Dittmar, and Lundblad (2005) emphasize low-frequency covariation in consumption and dividends as a source of risk. Similarly, Hansen, Heaton, and Li (2008) and Bansal, Dittmar, and Kiku (2009) investigate cointegration of consumption and dividends as a source of risk. With the evidence in these papers in mind, we estimate risk exposures by regressing cumulated portfolio returns on cumulated innovations in consumption growth and its volatility,

$$\prod_{j=0}^{K-1} R_{i,t-j} \quad = \quad a_i + \beta_{i,\eta} \sum_{j=0}^{K-1} \hat{\eta}_{t-j} + \beta_{i,w} \sum_{j=0}^{K-1} \hat{w}_{t-j} + e_{i,t}, \tag{8}$$

for different windows K, where $R_{i,t-j}$ is the gross real return on portfolio i.

The consumption measure that we use in this paper is the standard consumption of nondurable goods and services. Data are converted to real using the personal consumption expenditure deflator and are expressed in per capita terms. The consumption growth series is the first difference of log per capita consumption, sampled at the quarterly frequency from the second quarter of 1947 through the first quarter of 2014. Data are obtained from the National Income and Product Account tables at the Bureau of Economic Analysis.

In our cross-sectional regressions, we consider models in which only level or volatility risk is priced in addition to the unrestricted model in which both consumption level and volatility risks are priced. For these restricted models, we estimate univariate versions of regression (15) to obtain risk exposures. These univariate risk exposures are reported in Tables 2 and 3 for a window $K = 4$. We demonstrate that this window appears to generate the best cross-sectional fit for the model; risk exposures with $K = 1, 2$, and 8 are available from the authors upon request.

Consumption level risk exposures are presented in Table 2. The estimates suggest patterns that are broadly consistent with patterns in average returns. For the portfolios in which top quantile portfolio returns exceed those of bottom quantile portfolio returns, book-to-market and past 12-month return, the top quantile level exposure beta exceeds that of the bottom quantile exposure beta. Similarly, for characteristic-sorted portfolios in which the pattern is reversed, specifically asset growth, market value, stock issuance, and total accruals, the bottom quantile level risk exposure exceeds that of the top quantile risk exposure. While the pattern is not monotonic in quantiles, the broad patterns in average returns and risk exposures suggest a positive relation between consumption level risk exposure and average returns.

Exposures to innovations in consumption volatility are presented in Table 3. We expect two features of consumption volatility exposures based on theoretical considerations. First, we expect consumption volatility exposures to generally be negative, reflecting the idea that equity pays off poorly in bad economic states associated with high volatility of consumption growth. Second, we expect assets that hedge, or at least have less vulnerability to this risk, to command higher prices. Thus, we expect a negative relation between consumption volatility exposure and average returns. The first conjecture is borne out in the data; 54 of 55 return exposures to consumption volatility innovations are negative, consistent with the interpretation of equity as a an asset that provides a poor hedge to bad economic states. The evidence with respect to the second conjecture is more mixed. The exposures of high asset growth portfolios, low book-to-market portfolios, and low past 12-month return portfolios are distinctly lower than their opposing extreme decile exposures, consistent with a price of volatility risk that is negative. However, the pattern is close to flat in stock issuance, and inverted in market value-sorted portfolio average returns. Moreover, the pattern in deciles is far from monotonic, with the most extreme (negative) exposures to consumption volatility risk for all characteristics other than market value occurring in intermediate deciles.

The conclusion that we draw from examining exposures to consumption level and volatility innovations is that the exposures are broadly consistent with predictions of a theoretical model of asset prices. Equities are positively exposed to consumption level innovations and negatively exposed to volatility innovations. There appears to be coarse evidence suggesting a positive premium for consumption level risk and somewhat weaker evidence for a negative premium for volatility risk. We explore this evidence more formally in the next section.

3.3 Cross-Sectional Regression Results

The standard approach to investigating whether risk exposures are related to average returns is the two-stage approach where returns are regressed on sources of risk and average returns are then regressed on the resulting risk exposure estimates. The first stage estimates are discussed in the previous section, we now examine cross-sectional regressions of the form

$$\bar{R}_i - \bar{R}_f = \gamma_0 + \gamma_\eta \hat{\beta}_{i,\eta} + \gamma_w \hat{\beta}_{i,w} + u_i, \tag{9}$$

where $\bar{R}_i$ is the time series average of the return on portfolio i, $\bar{R}_f$ is the mean real quarterly compounded return on a Treasury Bill closest to one month to maturity from CRSP, and $\hat{\beta}_{i,\eta}$ and $\hat{\beta}_{i,w}$ are first stage estimates of univariate regressions of portfolio i's return on the mean and volatility innovations, η_t and w_t, respectively. In addition to the unrestricted model above, we also examine specifications where we consider the explanatory power of mean innovation and volatility innovation risks alone, restricting $\gamma_\eta = 0$ and $\gamma_w = 0$, respectively.

Results of the cross-sectional regressions are presented in Table 4. We present a total of four specifications. The specifications vary across restrictions on the prices of risk (i.e. $\gamma_w = 0$, $\gamma_\eta = 0$, and unrestricted), and in the number of periods over which innovations and returns are compounded. We examine four periods, $K = 1, 2, 4, 8$. In the case of $K = 1$, we are only allowing for the contemporaneous relation between returns and consumption level and volatility innovations. In the remaining versions, lower frequency covariations become important. In each case, we present t-statistics using standard errors corrected for first stage estimation error as in Shanken (1992) and, in parentheses under the R^2 the 95% critical value of the model R^2 under the null that the risk measures are unrelated to the average returns. This critical value is motivated by the recommendations of Lewellen, Nagel, and Shanken (2010), who suggest that the cross-sectional R^2 may overstate the model fit.[4]

[4]The critical value is calculated by generating 5000 random samples with 238 time series observations of two normally distributed variables with mean zero and standard deviation σ_η and σ_w to match sample standard deviations of the mean and volatility innovations. We regress returns on our sample assets on the random variables, and then perform second stage regressions of the mean returns on the resulting regression coefficients. Adjusted R^2 for the second stage regressions on the simulated risk measures are used to construct the null distribution of the adjusted R^2.

In Panel A, we consider the case in which $K = 1$, which corresponds to a traditional consumption CAPM in which risk exposures are captured by the covariance of returns with consumption growth, and an extension in which volatility innovations are priced as well. The table demonstrates that a simple consumption CAPM performs surprisingly well at describing cross-sectional variation in this set of average returns. The point estimate for the price of consumption risk, 0.442, is positive and statistically significantly different than zero. The regression adjusted R^2 suggests that the model captures 38% of cross-sectional variation in average returns. While this R^2 is does not exceed the 95% critical value implied by Monte Carlo simulations, it does exceed the 90% critical value, suggesting that the performance of the model is not simply a statistical accident.

The second column of Panel A presents results when the only priced source of risk is the innovation to the volatility of consumption growth. As shown in the table, this model explains a non-trivial fraction of variation in average returns, with a cross-sectional adjusted R^2 of nearly 14%. The point estimate for the price of volatility risk is negative, as expected, but the point estimate cannot be statistically distinguished from zero. Further, the intercept in the regression is large and statistically different from zero. The results suggest that consumption volatility risk alone cannot capture cross-sectional variation in this set of asset returns.

In the third column of Panel A, we present results for the unrestricted model, where both consumption growth innovations and the innovation in the volatility of consumption growth are allowed to bear prices of risk. Again, the price of consumption growth risk is positive, and very similar to the restricted model in magnitude at a point estimate of 0.455. The coefficient is statistically significantly different than zero at conventional significance levels. The price of volatility innovation risk is again negative, but although the t-statistic increases to 1.506, the coefficient cannot be distinguished from zero at conventional significance levels. While the model improves on the basic consumption CAPM with an adjusted R^2 of 43.65%, the improvement indicates that the addition of volatility risk exposure explains only an additional 5% of the cross-sectional variation in average returns. While this improvement is not zero, it suggests that the level innovation exposure is the primary source of priced risk in this cross section.

Comparing Panels B-D, varying $K = 2, 4, 8$, the results are qualitatively similar. A model with a single exposure to consumption growth risk performs surprisingly well in explaining cross-sectional variation in returns. Volatility exposures alone are generally statistically insignificant, although negative as suggested by theoretical considerations. Incorporating both volatility and level consumption risk exposures in the model improves the fit of the model, but only marginally, from around 2-5%. Notably, however, in the cases in which returns and consumption innovations are cumulated over more quarters, the price of volatility innovation risk becomes statistically distinguishable from zero in the unrestricted model.

The best performance of the model in terms of adjusted R^2 is in the case where $K = 4$, as exhibited in Panel C. In this case, the model with where only consumption level innovation risk exposure is priced produces a good fit for cross-sectional variation in average returns. The price of consumption level innovation risk is 0.578, and the coefficient is statistically different than zero as indicated by a t-statistic of 3.069. The regression adjusted R^2 is 64.11%, suggesting that the model captures nearly two-thirds of the cross-sectional variation in average returns across these 55 portfolios. Moreover, the adjusted R^2 is greater than the 40.90% critical value for a single-factor adjusted R^2 with no relation to average return. Finally, the point estimate for the intercept, 0.189, is not statistically distinguishable from zero. This evidence suggests that a single-factor consumption-based model provides a good description of the cross-sectional variation in average returns of these portfolios.

In the third column of Panel C, we present results when we allow both consumption growth level and volatility innovation risks to be priced. The incorporation of exposures to consumption volatility risk do result in an improved fit of the model. The price of consumption growth innovation risk remains positive and statistically significant, and the price of volatility innovation risk is negative and statistically significant. The intercept cannot be distinguished from zero, suggesting that the model fits the data well, and the adjusted R^2 increases to 67%, which exceeds the 95% critical value of 54%. This 67% adjusted R^2, however, represents an increase of less than 3% relative to the restricted model in which only consumption growth innovations are priced. As a result, while the model improves statistically on a single-factor model, the improvement is not of substantial economic magnitude.

We proceed with the single-factor consumption model with estimates in the first column of Panel C for the remainder of our paper. Increasing the window over which innovations and returns are cumulated to $K = 8$ results in a small deterioration in model fit. The model has the advantage of being parsimonious, and consistent with stochastic discount factors implied by either CRRA utility or Epstein and Zin (1989) utility. We can consider this model to be a straightforward consumption CAPM, with only the variation that consumption growth risk exposures are measured using low-frequency covariation of consumption growth with returns.

The fit of the model is depicted in Figure 1, and we report the magnitude of pricing errors in Table 5. The figure depicts predicted average returns on the x-axis and actual average returns on the y-axis; in a perfect model fit all points would plot on the 45-degree line. As suggested by the model adjusted-R^2, the fit is quite good, but not perfect. Both Panel B of Table 4 and Figure 1 suggest that the model has particular difficulty with a few portfolios in our sample, most notably those in the first three past 12-month return deciles. Overall, the mean absolute error of the pricing model is 34 basis points per quarter, and we cannot reject the null that the errors are zero using the χ^2 test discussed in Cochrane (2005). Thus, we conclude that a model with priced exposures to consumption risk provides a good description of cross-sectional variation in average returns across the six characteristics examined in our study.[5]

4 Using Characteristics to Estimate Risk Exposures

4.1 Mapping Characteristics into Risk Exposures

With the previous section's evidence that a single beta model incorporating consumption growth level risk exposures fits the cross-section of average returns well, we next turn to investigating the relation between the risk exposures of this model and characteristics. As discussed in Section 2.1, we hypothesize that the reason that portfolio characteristics are related to average returns is through the link between these characteristics and their exposures to risk in the stochastic discount factor. While the exact mapping is unknown, as a starting point, we assume that there is a linear relation between portfolio risk exposures and characteristics,

$$\left(\hat{\beta}_{p,\eta,t} - \bar{\hat{\beta}}_t\right) \quad = \quad \boldsymbol{\delta}'_{p,\eta,t}\left(\mathbf{x}_{p,t} - \bar{\mathbf{x}}_t\right) + e_{p,\eta,t} \tag{10}$$

where $\mathbf{x}_{p,t}$ is a vector of the characteristics on which the portfolios are formed. In this expression, $\hat{\beta}_{p,\eta,t}$ is the portfolio consumption growth innovation risk exposure, estimated using information available to time t. Thus, in this expression, risk exposures are allowed to vary over time due to changing characteristics, $\mathbf{x}_{p,t}$, as well as due to a time-varying mapping of characteristics into risk exposures, $\boldsymbol{\delta}_{p,\eta,t}$. We cross-sectionally de-mean variables to remove any time trends that might generate spurious time variation in risk exposures.

The specific procedure by which we construct portfolio-level estimates of the relation between characteristics and betas proceeds as follows:

1. We begin with a subsample of our consumption data from the third quarter of 1953 through the third quarter of 1983. We calculate demeaned consumption growth over this time period to obtain the consumption growth innovation. Innovations to the level of consumption growth are summed over four quarters to obtain a series of smoothed innovations from the fourth

[5] In untabulated results, we compare the performance of the model explored in this paper to alternative consumption- and factor-based models. The consumption alternatives that we consider are the conditional CCAPM of Lettau and Ludvigson (2001), the ultimate consumption risk model of Parker and Julliard (2005), the cash flow consumption risk model of Bansal, Dittmar, and Lundblad (2005), and the durable consumption goods model of Yogo (2006). The evidence suggests that the consumption-based framework presented in this paper outperforms these alternatives. We do not examine other consumption-based models such as the calendar year end consumption model of Jagannathan and Wang (2007) or Savov (2011) due to their use of annual data. The model also provides superior cross-sectional fit to the five-factor model of Fama and French (2014) and the four-factor model of Hou, Xue, and Zhang (2014). These results are available from the authors upon request.

quarter of 1954 through the third quarter of 1983, representing 120 quarters or 30 years of data.

2. Cumulative overlapping annual portfolio returns for the 120 quarters spanning the fourth quarter of 1954 through the third quarter of 1983 are regressed on the smoothed level and volatility innovations. The regression coefficients represent the initial estimates of risk exposures $\beta_{p,\eta,t}$ and $\beta_{p,w,t}$ for the portfolios. We then regress the resulting cross-sectionally de-meaned risk exposures on the cross-sectionally de-meaned portfolio characteristics, $(\mathbf{x}_{pt} - \bar{\mathbf{x}}_t)$ for each month September, 1983 through November, 1983, and retain the regression parameter estimates, $\boldsymbol{\delta}_{p,\eta,t}$.

3. We roll forward one quarter, augmenting the consumption growth and return data by the new quarter's observations, and re-estimate the model of consumption dynamics and accompanying risk exposures. We then regress characteristics for each month December, 1983 through February, 1984 on the risk exposures. Since our financial statement characteristics use the timing convention of Fama and French (1993), these characteristics are based on financial statement data known as of June, 1983. We continue this procedure, expanding the window over which the model of consumption dynamics and regression of returns on innovations is estimated until reaching the end of the sample.

In order to get some sense of how the characteristics and risk exposures relate to one another, in Table 6 we present average coefficients, $\bar{\boldsymbol{\delta}}_{p,\eta}$ with standard errors calculated as in Fama and MacBeth (1973) and average regression adjusted R^2. The coefficients on characteristics appear to conform with the results of the cross-sectional regressions. The book-to-market ratio and past 12-month return are positively related to risk exposures, while market value, stock issuance, and total accruals are negatively related to risk exposures. Only asset growth is somewhat confounding, with a positive exposure. All of the characteristics other than book-to-market ratio have statistically significant explanatory power for variation in level risk exposures. Finally, the characteristics explain a substantial portion of cross-sectional variation in risk exposures, with an average adjusted R^2 of 59.47%, and a range from 40.54% to 74.46%.

In Figure 2, we plot the cross-sectional mean beta over time, as well as time series of the level innovation beta regression coefficients for each characteristic, where coefficients are averaged over 12 months. The figure also plots NBER recessions as grey bars. The cross-sectional average beta, shown in Panel A, is relatively high in the 1980s, but decreases until the early 1990s recession. During the recession, it increases again, and drops substantially during the 1990s expansion. The average beta rises after the 2000s recession until 2003, where it remains fairly steady until the 2008-2009 recession, where it increases dramatically to nearly 4.4. After the recession, it drops off again, but remains at a level closer to its 1980s levels than that exhibited during the 1990s and

2000s. To the extent that time variation in the mean beta captures variation in risk premia, the results appear to be reasonable, generally high in times associated with weak economic conditions and low in times of poor conditions. However, given our fairly limited time series, we maintain caution in interpreting the results in terms of business cycle variation.

The coefficients on characteristics also exhibit considerable time series variation. It is difficult to select one unifying theme for the coefficients, and difficult to interpret their behavior in terms of the business cycle. Most of the coefficients do appear to exhibit some mean-reverting behavior, with extended periods above the mean followed by revisions downward. The coefficients on market value are the exception, appearing to exhibit an upward trend. Beyond noting this observation, it is difficult to interpret the coefficients' time series behavior. Although the coefficients are clearly sensitive to business cycle variation, they do not uniformly increase or decrease through recessions and expansions.

To conclude, the evidence in this section suggests to us that characteristics are in fact associated with exposures to consumption growth innovation risks. These risks appear to be driven by some common features of the data, and exhibit some form of cyclicality, although it is not clear that this represents exposure to cycles. However, there are interesting patterns in time-variation in the relation between characteristics and betas that suggest differing quantities of risk associated with different characteristics at different points in time.

4.2 Characteristics and Firm-Level Exposures to Macroeconomic Risk

In the previous section, we verified the relation between risk exposures and characteristics at the portfolio level. We hypothesize that the relation that holds at the portfolio level also holds at the firm level. That is, the relation between firm-level exposures and portfolio-level exposures and characteristics is given by

$$\begin{aligned}
\beta_{i,\eta,t} - \bar{\beta}_{\eta,t} &= \boldsymbol{\delta}'_{it}\left(\mathbf{x}_{it} - \bar{\mathbf{x}}_t\right) + u_{it} \\
\beta_{p,\eta,t} - \bar{\beta}_{\eta,t} &= \sum_{i=1}^{N} \omega_{i,t-1}\left(\boldsymbol{\delta}'_{i,t}\left(\mathbf{x}_{it} - \bar{\mathbf{x}}_t\right) + u_{it}\right) \\
&= \boldsymbol{\delta}'_{p,t}\left(\mathbf{x}_{pt} - \bar{\mathbf{x}}_t\right) + u_{pt},
\end{aligned}$$

where i indexes firms, p represents portfolios, and ω_i is the weight on asset i in the portfolio. Consequently, by estimating the coefficients $\boldsymbol{\delta}_t$ at the portfolio level, we can use the coefficients to retrieve firm-specific risk measures at the firm level.[6] This translation between the portfolio and the firm level relations of risk exposures and characteristics is similar to the use of portfolio-level

[6]When forming firm-level risk exposures, we add back the portfolio mean risk exposure for the time period, $\bar{\beta}_t$.

CAPM betas to measure firm-level betas in Fama and French (1992).

We implement this idea by using firm-level characteristics and portfolio-level coefficients to calculate firm-level betas. As above, we average coefficients over 12 months to reduce some of the estimation noise resulting from the portfolio-level regressions. We use firm-level characteristics to form portfolios that are characterized by differences in *ex ante* consumption risk exposure. Specifically, each month t, using the coefficients calculated for month t and characteristics as of the prior June, except the past 12-month return, we calculate a consumption growth innovation exposure for every firm. We rank firms into quintiles on the basis of this exposure and form both equally-weighted and value-weighted portfolios. We are particularly interested in three questions. First, does sorting firms into portfolios on the basis of *ex ante* predicted betas produce a positive risk premium? Second, do the resulting portfolios exhibit *ex post* risk exposures that are consistent with the *ex ante* ranking? Finally, can we characterize the time series variation in the *ex ante* risk exposures of these portfolios in an economically meaningful way?

In Table 7, Panel A, we present the results of regressions of monthly returns on the predicted betas. The panel presents the mean intercept and slope coefficient, with t-statistics calculated using the procedure in Fama and MacBeth (1973). The regressions suggest that the calculated betas bear a positive risk premium as expected; the slope coefficient of 0.221 is highly statistically significant with a t-statistic of 3.782. The coefficient is smaller than those reported in the cross-sectional regressions in Table 4, but of similar magnitude. Further, the qualitative conclusion of a positive and statistically significant price of risk is consistent with our portfolio-level regression results.

In Table 7, Panel B, we present mean returns, the *ex ante* beta, and the *ex post* beta for five value-weighted portfolios. As shown in the table, average returns increase monotonically from the first through fourth quintiles, but fall slightly in the fifth quintile. The overall impression is of a positive relation between average returns and consumption risk exposures, consistent with the cross-sectional regression evidence, but the relation is slightly imperfect. Similarly, *ex post* risk exposures increase monotonically for the first through fourth quintiles, but fall slightly in the fifth quintile. The magnitudes of these betas are similar to the *ex ante* betas, and the generally increasing pattern suggests that we have some success in capturing variation in *ex post* betas through our *ex ante* characteristic betas.

In Panel C of Table 7, we present mean returns, the *ex ante* beta, and the *ex post* beta for five equally-weighted portfolios. In contrast to the results in Panel B, returns increase perfectly monotonically from quintile one to quintile five. The average return on the fifth quintile portfolio exceeds that of the first quintile portfolio by 91 basis points per month, and the difference is statistically significantly different than zero (t-statistic=4.16). Further, the *ex post* betas are again of similar magnitude as the *ex ante* betas, and also increase monotonically across quintiles. These results suggest that the deviations from monotonicity in the value-weighted portfolio returns may be related to some influential large firms with high predicted *ex ante* betas. Most importantly, the results suggest that in equally-weighted portfolios, our *ex ante* procedure produces a consistent *ex post* beta ranking.

The time series of the *ex ante* consumption betas calculated using characteristics is depicted in Figure 3. For brevity, we present betas for equally-weighted portfolios; results for value-weighted portfolios are similar. As with the coefficients, the betas exhibit some degree of low frequency variation. This variation appears to coincide loosely with the business cycle. The low consumption risk portfolio (first quintile) beta appears to exhibit increases associated with each of the three recessions in our sample, with decreases in the middle of the 1990s, 2000s, and 2010s expansions. The high consumption risk portfolio (fifth quintile) beta exhibits a steady decrease from the 1980s through the 1990s, which is reversed in the 2000s. The beta increases dramatically in the recession of 2007-2009. Finally, it seems that time-series variation in the betas likely comes from a common source. The extreme quintile betas are 67% correlated with one another, and correlations with adjacent quintiles are substantially higher. In our final section, we will employ industry portfolios to help shed light on our methodology and the sources of the implied cross-sectional an time-series variation in consumption risk exposures.

4.3 Factor Risk Exposures of Consumption Beta Portfolios

Our final analysis in this section is to consider the exposure of our beta-sorted portfolios to popular return-based factor models to see if the returns on these portfolios are associated with premia for common statistical factor risks. Fama and French (2014) and Hou, Xue, and Zhang (2014) propose factor models designed to capture a number of return patterns observed in the data and common to the characteristics on which we form portfolios. We investigate whether these factor models capture variation in the consumption beta-sorted portfolios. The factor models are estimated using time-series regressions of excess returns of the beta portfolios on the set of factors with each model:

$$\begin{aligned} R_{p,t+1} - R_f &= \alpha_p^{FF} + \beta_{p,MRP} R_{MRP,t+1} + \beta_{p,SMB} R_{SMB,t+1} + \beta_{p,HML} R_{HML,t+1} \\ &\quad + \beta_{p,CMA} R_{CMA,t+1} + \beta_{p,RMW} R_{RMW,t+1} + \epsilon_{p,t+1}^{FF} \end{aligned} \tag{11}$$

$$\begin{aligned} R_{p,t+1} - R_f &= \alpha_p^{HXZ} + \beta_{p,MKT} R_{MKT,t+1} + \beta_{p,ME} R_{ME,t+1} + \beta_{p,IA} R_{IA,t+1} \\ &\quad + \beta_{p,ROE} R_{ROE,t+1} + \epsilon_{p,t+1}^{HXZ}, \end{aligned} \tag{12}$$

where the first model is proposed in Fama and French (2014) and the second in Hou, Xue, and Zhang (2014).

The Fama and French (2014) five-factor model draws on evidence from Novy-Marx (2013) and

Aharoni, Grundy, and Zeng (2013) suggesting that profitability and investment bear risk premia in the cross-section. They use this evidence to support augmenting the Fama and French (1993) three-factor model with an investment and profitability factor. We use book-to-market (HML), investment (CMA), and profitability (RMW) factors that are formed by using portfolios sorted on the intersection of size and book-to-market, investment, or profitability quantiles. Specifically, firms are sorted based on market values above or below median for the cross-section, and below 30th, 30th-70th, and above 70th percentiles on the characteristic in question. Details on variable formation can be found in Fama and French (2014), and data are obtained from Kenneth French's website at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.[7] Hou, Xue, and Zhang (2014) propose a four-factor model that is similar to the five-factor model of Fama and French (2014) in that it includes an investment (IA) and profitability factor (ROE) in addition to a size (ME) and market (MKT) factor. However the authors appeal to producers' first order conditions for investment to justify the presence of the factors in the model, noting that the return on investment will be a function of profitability and investment intensity. Details of the construction of these factors is provided in Hou, Xue, and Zhang (2014).[8]

Results of this analysis are presented in Table 8. In Panel A, we present results for the Fama and French (2014) five-factor model and in Panel B we present results for the Hou, Xue, and Zhang (2014) model. We use the equally-weighted characteristic beta portfolios and equally-weighted portfolios to form the Fama and French (2014) factors.[9] Results in Panel A suggest that the five-factor model has difficulty pricing the returns on these portfolios. Four of the five intercept terms are significantly different than zero; those of the first two quintiles are negative and those of the top two quintiles are positive. The difference in extreme quintile intercepts is 93 basis points per month, statistically significantly different than zero at less than the 1% critical level (t-statistic=4.769). Thus, there is a statistically significant and economically large premium associated with the consumption beta-sorted portfolios that is unrelated to the five factors in the model.

Overall, the five factor model fares very well in capturing time series variation in portfolio returns. The model R^2 exceed 90% for each of the five quintiles of consumption betas. Most of the explanatory power appears to be coming from three factors: the market risk premium, the size factor, and the investment factor. All five slope coefficients for the market risk premium are statistically significantly different than zero and interestingly, the slope coefficients are monotonically decreasing in quintiles, such that the high minus low consumption beta excess return is negatively exposed to market risk. The slopes with respect to the size factor and the investment factor are monotonically positively increasing across quintiles, suggesting that high consumption beta port-

[7]Thanks to Ken French for making these data available.

[8]Thanks to Lu Zhang and Chen Xue for providing us with these data.

[9]The Hou, Xue, and Zhang (2014) factors are based on value-weighted returns. Results using the value-weighted characteristic beta portfolios are qualitatively similar to those with equally-weighted returns.

folios tend to covary highly with small firms and low-investment firms. The profitability factor bears statistically significant slopes only in the intermediate quintiles, and the value factor bears no statistically significant slopes. This latter result echoes the finding of Fama and French (2014) that HML and CMA may capture similar covariation in returns.

Results in Panel B for the Hou, Xue, and Zhang (2014) four-factor model are similar. Intercepts are increasing across quintiles, with a statistically significant premium of 91 basis points for high consumption beta portfolios in excess of low consumption beta portfolios (t-statistic=4.397). As in the five-factor model, the consumption beta sort generates a monotonically decreasing sort in exposures the the market factor, and monotonically increasing sort in exposure to the size factor. However, there is no discernible pattern in the investment and earnings factors. Loadings for the middle three quintiles on the investment factor are statistically significant and positive, but extreme portfolios do not load significantly on this factor. All five quintile portfolios load negatively and significantly on the earnings factor, but the pattern in loadings is U-shaped. Last, the factors explain somewhat less of the time series variation in the consumption beta-sorted portfolio returns, but the model still explains in excess of 80% of time series variation for all five portfolios under consideration.

In conclusion, we suggest that there are several points to take away from this analysis. The portfolios that we form to maximize cross-sectional variation in consumption betas are based on consumption betas predicted by firms' asset growth, book-to-market ratio, market value, past 12-month return, stock issuance, and total accruals. Hou, Xue, and Zhang (2014) note that all six of these characteristics can be thought of as related to a firm's investment policy or profitability. As such, one would expect models that incorporate these factors to provide a good description of the returns. We show that factors based on investment and profitability considerations, in addition to other commonly proposed factors, do indeed describe time-series variation in the returns on our portfolios quite well.

However, these approaches suffer from three core problems. First, the expected returns on these portfolios cannot be fully characterized by the factor exposures, suggesting the presence of relevant pricing components in our consumption beta-sorted portfolio returns that are independent of that in characteristic-based statistical factors. Second, the models remain statistical, whereas our mapping from portfolio risk exposures to firm characteristics is rooted in consumption-based asset pricing, even if reduced-form. Finally, these factor models require one time-series to estimate the (constant) risk exposures underlying their model; this is a critical problem in the face of time variation in firm-level risk exposures and costs of capital that our methodology is designed to overcome.

5 Industry Costs of Capital

Our final analysis in the paper is an examination of industry portfolios. Industries provide a natural laboratory in which to shed light on our firm-level methodology for measuring risk exposures and costs of capital. As discussed in the introduction, one of the motivations for our study is the finding in Fama and French (1997) that industry risk exposures are themselves quite difficult to estimate. However, relative to firm equity returns, industry portfolio returns enjoy the usual diversification effects, but - similar to firms - they also likely exhibit significant cross-sectional and time-series variation in industry characteristics along with temporal variation in consumption risk exposures. While we view our contribution as providing a methodology to evaluate consumption risk exposures at the most disaggregated levels, industry portfolios provide a natural laboratory in which to evaluate our approach.

We construct 24 industry portfolios based on Standard and Poor's Global Industrial Classification System (GICS) industry groups, obtained from Compustat. For each firm, we compute an *ex ante* risk exposure as in the previous section, using the portfolio-level coefficients retrieved using the 55 characteristic-sorted portfolios. We form value-weighted portfolios on the basis of industry groups, and examine value-weighted *ex ante* betas. Average betas by industry group are reported in Table 9, together with the results of Fama and MacBeth (1973) regressions of industry portfolio returns at each point in time t on the portfolio beta as of formation at time $t-1$. Data are sampled at the monthly frequency over the time period June, 1984 through December, 2012.

Panel A of Table 9 reports average returns, mean *ex ante* betas, and standard deviations of betas for industry portfolios. The industry portfolios have a fairly large dispersion in average returns, ranging from 80 basis points per month for Real Estate to 170 basis points per month for Pharmaceuticals. However, Pharmaceuticals have a relatively low mean beta and Real Estate has a relatively high mean beta, so the unconditional relationship across average returns and consumption betas may be problematic. Indeed, the correlation between average returns and consumption betas is negative, albeit statistically insignificant.

This weak relationship may be a function of the high degree of temporal variation in consumption betas. The third column presents the high degree of consumption beta volatility. Moreover, as shown in Panel B, Fama and MacBeth (1973) regressions of returns on the *ex ante* betas exhibit a positive and statistically significant risk premium that is of similar magnitude to those reported earlier in the paper. This evidence points to the danger of assuming constant risk exposures in evaluating industry (or firm) expected returns. Consumption risk is significantly priced for firm and industry equity returns, but the pronounced degree of variation in consumption risk exposure masks this important feature of the data. Our methodology circumvents this limitation of the traditional asset pricing approach.

The evidence in this section suggests that time variation in the exposure of industry returns to consumption risk is an important factor. While we observed that accounting for this variation uncovers important cross-sectional pricing effects, we also want to use the industry setting to better understand the principal sources of this beta variation through time to shed light on the mechanics underlying our methodology.

First, we plot the *ex ante* consumption betas of the 24 industry groups in Figure 4. We do indeed observe significant variation across in consumption betas through time across all industries. We might expect that betas, and consequently the associated discount rates, will tend to be high during contractions and low during expansions. Across all industries, there does appear to be a marked increase in consumption betas during the financial crisis of 2007-2009, and most industries also appear to exhibit a general decreasing trend in consumption betas during the expansion of the 1990s. Still, it is hard to conclude from this plot that the risk exposures are decisively countercyclical.

Since the industry portfolio set is relatively contained in comparison to the firm-level analysis, we next examine "variance decompositions" of industries' risk exposures by evaluating the role for the various industry-level characteristics that are driving our consumption beta construction:

$$\begin{aligned} Var\left(\beta_{p,t}\right) &= Var\left(\bar{\beta}_t\right) + Var\left(\delta_{AG,t} AG_{p,t}\right) + Var\left(\delta_{BM,t} BM_{p,t}\right) + Var\left(\delta_{MV,t} MV_{p,t}\right) \\ &\quad + Var\left(\delta_{P12,t} P12_{p,t}\right) + Var\left(\delta_{SI,t} SI_{p,t}\right) + Var\left(\delta_{TA,t} TA_{p,t}\right) + P_{p,t}, \end{aligned} \tag{13}$$

where $P_{p,t}$ are covariance terms among the components of the risk exposures, and for convenience all characteristics are assumed to be cross-sectionally de-meaned. We present the proportion of variance accounted for by each component in Table 10.

Table 10 shows interesting differences across industries in the sources of variation in industry risk exposures. For all industries, variation in the overall mean beta is a large driver of variation in the industry beta, averaging 71.5% and accounting for between 29% of variation for Telecommunications and 116% for capital goods. The second biggest determinant is the past 12-month return, accounting for 21.7% of variation, and ranging driving 7.3% of Commercial Services beta variation to 48.1% of Energy beta variation. After the past 12-month return the average drivers of variation in beta in descending order of contribution are market value, stock issuance, total accruals, book-to-market ratio, and asset growth. Asset growth has a significant impact on variation in Healthcare risk exposure (7.6%), the book-to-market ratio on Pharmaceuticals (14.2%), stock issuance on Pharmaceuticals (21.0%), and total accruals on Diversified Financials, Automobiles, and Transportation (7.0%, 6.6%, and 6.0%, respectively). One key takeaway is that the methodology relies on a number of different industry (or firm) characteristics to fully map out the consumption beta through time.

Finally, with industry-level time-varying consumption betas in hand, we examine implied costs of capital for industry portfolios under two assumptions. We first assume that the price of consumption growth risk is constant, with the quantity given by the parameter estimate in Table 4. Under this assumption, time variation in an industry's risk premium is driven only by variation in the consumption risk exposure described above. Alternatively, we allow both the consumption risk exposure and the price of risk to vary over time. In order to measure the time-varying price of risk, we utilize the time series of estimates of prices of risk implied by the rolling procedure in Section 4.2. That is, we take point estimates, $\hat{\gamma}_t$ from expanding window regressions

$$\frac{1}{t}\sum_{j=t-1}^{0}(R_{p,t-j}-R_{f,t}) = \gamma_{0,t} + \gamma_{\eta,t}\hat{\beta}_{p,t} + u_{p,t},$$

where $\beta_{p,t}$ is the consumption risk exposure estimated using data from time 0 to time t. In this case, time variation in risk premia arises from both variation in the exposure to risk and the price of risk.

We plot the time series of the price of risk In Figure 5. As shown in the plot, there appears to be strong countercyclical variation in the price of risk. The estimate decreases steadily through the 1980s expansion and jumps in the early 1990s recession, before decaying into the late 1990s. The price of risk jumps again in the late 1990s and stays elevated through the early 2000s before declining again. Finally, the price of consumption risk exhibits a pronounced increase associated with the recession of 2007-2009. These prices of risk vary between a range of 0.40 and 0.63. Given the evidence reported above supporting countercyclical risk exposures, we surmise that incorporating a time-varying price of risk will intensify the counter-cyclicality of the cost of industry capital.

Averages of risk premia calculated under the assumption of constant and time-varying prices of consumption risk are presented in Table 11. As shown in the table, costs of capital vary substantially over time and across industries. The lowest average risk premium in both the constant and time-varying cases is that of the Utilities industry; the quarterly risk premium of 1.60% suggests an average risk premium of 6.38% per annum and the average of 1.43% in the time-varying case suggests an average risk premium of 5.72% per annum. The highest average risk premium is for the Consumer Services sector, with an implied annual risk premium on average of 8.34% in the constant beta case and 7.46% in the time-varying beta case. The global minimum risk premium for the sample occurs for the Semiconductor industry in the fourth quarter of 1996, at 3.71% per annum in the constant price of risk case and 2.57% in the time-varying price of risk case. The global maximum is 13.28% for the Media industry in the second quarter of 2010 (13.69% with time-varying price of risk).

We examine the counter-cyclicality of risk premia more closely by explicitly considering the relation between risk premier and consumption growth. Specifically, we estimate parameters in the following regression,

$$\hat{rp}_{p,t} = a_p + d_p I_{recession,t} + c_p \Delta c_t + v_{p,t}, \tag{14}$$

where $\hat{rp}_{p,t}$ is industry p's risk premium over a calendar quarter, $I_{recession,t}$ is an indicator variable that takes the value one if the economy is in NBER recession during the quarter t and zero otherwise. Results are shown in Table 12 for the case in which the price of risk is allowed to vary over time. Results are qualitatively similar for the constant price of risk case The table shows that the point estimate for the sensitivity of risk exposures to consumption growth is negative for each of the 24 industry groups, with eighteen of the point estimates statistically significant at conventional levels. This evidence is consistent with the idea of countercyclical risk premia; risk premia are high when consumption growth is low. However, the point estimates of d_p are uniformly negative, suggesting that betas, and thus costs of capital, are on average lower in NBER recessions. Thus, risk exposures move counter cyclically in the sense that they tend to be higher when consumption growth is low, but this variation is not perfectly captured by NBER recessions.

The industries are ordered in Table **??** based on the magnitude of the industry beta's exposure to consumption growth. We interpret this ordering as indicating which industries are the most "cyclical," in that their costs of capital are most sensitive to changes in consumption growth. Near the top of the list are industries that conventional wisdom would suggest tend to be more cyclically sensitive, such as Banks and Consumer Durables, and toward the bottom are industries that are viewed as less cyclical, such as Food, Beverage, and Tobacco and Food and Staples Retail. Some of the results are somewhat surprising, however. For example, Utilities appears to be a relatively cyclical industry, in the top third of sensitivities, whereas capital goods appears to be relatively cyclical, in the bottom third of industry sensitivities.

6 Conclusion

Consumption-based asset pricing is an essential link between standard economic theory and finance, but it has been difficult to implement practically due to the challenge of measuring low-frequency consumption risk exposures. Despite recent progress in consumption-based asset pricing, this class of models is not widely used for return benchmarking, risk measurement, or the firm-level analyses of the cost of capital.

To fill this void, we provide a novel framework that permits the blending of portfolio-level consumption risk exposures with asset characteristics to better characterize and predict time-varying firm- and industry- level exposures to consumption risks. Using a model that explains roughly two-thirds of cross-sectional variation in a set of 55 portfolios sorted on six firm characteristics, we implement a procedure to forecast firm- and industry-level exposures to consumption risks.

We find that portfolios sorted on these consumption risks generally exhibit *ex post* exposures to consumption risks that are consistent with *ex ante* predictions. Further, the resulting time-varying costs of capital are plausible.

The procedure proposed in this paper has the potential to be applied to a wide range of uses for the imputation of cost of capital. Implied risk premium estimates could be used for benchmarking mutual fund performance, evaluating the profitability of trading strategies, and estimating required rates of return. The advantage of using this framework is that it is firmly rooted in economic theory, specifically the consumption-based pricing models of Lucas (1978) and Breeden (1979). As such, it represents an economic-based alternative to risk adjustment and cost of capital estimation based on *ad hoc* statistical return factors.

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Table 1: Average Returns

Table 1 depicts average returns on a set of 55 portfolios formed on the basis of six characteristics. Portfolios are formed on asset growth (AG), book-to-market ratio (BM), market value (MV), past 12-month return (P12), net stock issues (SI), and total accruals (TA). We form value-weighted portfolios based on deciles of six characteristics and quintiles of net stock issues. Data are sampled at the quarterly frequency from September, 1953 through December, 2012. Returns are deflated to real using the PCE deflator from the NIPA tables at the Bureau of Economic Analysis.

Dec/Quint	AG	BM	MV	P12	SI	TA
1	2.79	1.92	3.66	-0.71	2.44	2.70
2	2.58	1.76	2.99	0.42	2.23	2.27
3	2.46	2.22	3.02	0.95	2.28	2.22
4	2.21	1.99	2.77	1.69	2.10	2.14
5	2.32	2.33	2.69	1.92	1.36	2.30
6	2.16	2.37	2.86	1.90		2.34
7	2.28	2.43	2.64	2.29		1.99
8	2.24	2.82	2.56	2.65		2.00
9	2.12	2.91	2.52	2.95		1.97
10	1.59	3.47	1.98	4.21		1.38

Table 2: Consumption Growth Innovation Risk Exposures

In Table 2, we present growth innovation risk exposures and standard errors from a regression of cumulative portfolio excess returns on cumulative consumption growth level innovations,

$$\prod_{j=0}^{7} R_{i,t-j} \quad = \quad a_i + \beta_{i,\eta} \sum_{j=0}^{7} \hat{\eta}_{t-j} + e_{i,t},$$

where $\hat{\eta}_t$ is the innovation in the level of consumption growth. Returns are on portfolios sorted on asset growth (AG), book-to-market ratio (BM), market value (MV), past 12-month return (P12), stock issues (SI), and total accruals (TA). We present point estimates of growth risk exposures, $\beta_{i,\eta}$ in Panel A and t-statistics for the estimates, calculated using the Newey-West correction with eight lags, in Panel B. Data are sampled at the quarterly frequency over the period September, 1953 through December, 2012.

Panel A: Estimates

Decile	AG	BM	MV	P12	SI	TA
1	3.81	3.12	6.71	0.29	3.66	4.68
2	2.66	2.07	5.31	2.81	3.55	3.57
3	2.55	2.16	4.43	2.53	3.65	3.16
4	2.81	2.09	4.43	2.18	3.31	2.91
5	2.75	3.06	4.21	2.38	2.35	2.54
6	3.00	3.38	4.07	2.07		2.21
7	4.13	3.99	3.73	2.43		3.05
8	3.18	3.66	3.03	3.07		3.57
9	3.20	3.30	2.79	4.29		3.82
10	2.53	4.41	3.19	6.92		1.81

Panel B: t-statistics

Decile	AG	BM	MV	P12	SI	TA
1	2.13	1.84	2.71	0.12	2.85	2.92
2	1.91	1.55	2.45	1.48	2.90	2.46
3	1.89	1.58	2.21	1.46	2.64	2.48
4	2.18	1.30	2.44	1.36	2.31	2.33
5	2.15	2.13	2.64	1.77	1.63	1.94
6	2.41	2.80	2.59	1.53		1.87
7	2.82	2.30	2.51	1.88		1.92
8	2.34	2.60	2.14	2.54		2.51
9	2.08	2.51	1.95	3.01		2.34
10	1.55	2.93	2.46	3.87		1.02

Table 3: Volatility Innovation Risk Exposures

In Table 3, we present volatility innovation risk exposures and standard errors from a regression of cumulative portfolio excess returns on cumulative volatility innovations,

$$\prod_{j=0}^{7} R_{i,t-j} = a_i + \beta_{i,w} \sum_{j=0}^{7} \hat{w}_{t+1} + e_{i,t},$$

where $\hat{w}_t$ is the innovation in consumption volatility. Consumption volatility is measured as the squared innovation in the level of consumption growth, $e\hat{t}a_t^2$, and is assumed to follow an AR(1). Returns are on portfolios sorted on asset growth (AG), book-to-market ratio (BM), market value (MV), past 12-month return (P12), stock issues (SI), and total accruals (TA). We present point estimates of growth risk exposures, $\beta_{i,\eta}$ in Panel A and t-statistics for the estimates, calculated using the Newey-West correction with eight lags, in Panel B. Data are sampled at the quarterly frequency over the period September, 1953 through December, 2012.

Panel A: Estimates

Decile	AG	BM	MV	P12	SI	TA
1	-4.04	-1.34	-0.56	0.54	-3.05	-2.40
2	-3.60	-1.36	-1.97	-1.92	-2.78	-3.40
3	-3.69	-3.75	-2.66	-4.19	-3.63	-3.70
4	-4.60	-4.69	-2.02	-4.25	-3.20	-2.47
5	-3.55	-3.51	-2.71	-3.07	-2.77	-3.87
6	-3.36	-3.51	-2.15	-2.63		-2.67
7	-4.19	-4.94	-2.07	-2.34		-3.78
8	-2.51	-3.01	-2.37	-2.28		-2.99
9	-1.08	-3.70	-2.72	-1.89		-3.52
10	-0.40	-3.27	-3.25	-1.19		-1.47

Panel B: t-statistics

Decile	AG	BM	MV	P12	SI	TA
1	-1.66	-0.51	-0.13	0.19	-1.40	-0.80
2	-1.67	-0.61	-0.51	-0.69	-1.40	-1.37
3	-1.88	-2.42	-0.83	-1.72	-1.58	-1.75
4	-2.83	-1.91	-0.63	-2.66	-1.18	-1.21
5	-1.71	-1.62	-1.00	-1.83	-1.06	-2.02
6	-1.70	-1.48	-0.80	-1.72		-1.53
7	-1.79	-1.55	-0.76	-1.28		-1.57
8	-1.11	-1.19	-0.95	-0.87		-1.05
9	-0.39	-1.49	-1.11	-0.53		-1.08
10	-0.13	-1.12	-1.53	-0.24		-0.60

Table 4: Cross-Sectional Regressions

Table 4 presents estimates of cross-sectional regressions of average excess portfolio returns on risk measures,

$$\bar{R}_i - \bar{R}_f = \gamma_0 + \gamma_\eta \beta_{i,\eta} + \gamma_w \beta_{i,w} + u_i,$$

where $\bar{R}_i$ is the average real quarterly return on a set of 55 portfolios formed on asset growth, book-to-market ratio, market value, past 12-month return, net stock issues, and total accruals, and R_f is the real quarterly compounded return on a Treasury Bill closest to one month to maturity. The independent variables $\beta_{i,\eta}$ and $\beta_{i,w}$ are slope coefficients from three versions of the first stage regression,

$$\prod_{j=0}^{K} R_{i,t-j} \quad = \quad a_i + \beta_{i,\eta} \sum_{j=0}^{7} \hat{\eta}_{t-j} + \beta_{i,w} \sum_{j=0}^{K} \hat{w}_{t+1} + e_{i,t},$$

where $\hat{\eta}_{t+1}$ is the innovation in the level of consumption growth and $\hat{w}_{t+1}$ is the innovation in consumption volatility measured as the AR(1) residual on the squared consumption growth innovation, $\hat{\eta}^2_{t+1}$. We present results based on single regressions of cumulative returns on cumulative consumption growth level innovations, single regressions of cumulative returns on cumulative consumption growth volatility innovations, and multiple regressions of cumulative returns on both consumption level and volatility innovations. Results are presented for cumulations over $K = 1, 2, 4, 8$ periods. The table presents point estimates and adjusted R^2 for three versions of the model: Model 1 with the restriction $\gamma_w = 0$, Model 2 with $\gamma_\eta = 0$, and an unrestricted version, Model 3. Standard errors corrected for first stage estimation bias following Shanken (1992) are presented in parentheses below the point estimates. Beneath the adjusted R^2, we present 95% critical values for adjusted R^2 from 5000 Monte Carlo simulations under the null that the independent variables have no explanatory power for the returns. Data are sampled at the quarterly frequency over the period September, 1953 through December, 2012.

Panel A: $K = 1$

	Model 1	Model 2	Model 3
γ_0	0.51	1.84	0.57
t-stat.	(1.88)	(16.94)	(2.16)
γ_η	0.44		0.46
t-stat.	(2.01)		(1.99)
γ_w		-0.52	-0.35
t-stat.		(-0.72)	(-1.51)
$\bar{R}^2$	38.20	13.77	43.65
Crit. Value	(43.07)	(43.48)	(56.26)

Panel B: $K = 2$

	Model 1	Model 2	Model 3
γ_0	0.19	1.97	-0.12
t-stat.	0.80	8.94	-0.45
γ_η	0.54		0.61
t-stat.	2.71		2.91
γ_w		-0.08	-0.28
t-stat.	-0.25	-1.70	
$\bar{R}^2$	56.63	-1.19	59.05
Crit. Value	(44.34)	(44.59)	(58.07)

Panel C: $K = 4$

	Model 1	Model 2	Model 3
γ_0	0.19	1.88	-0.22
t-stat.	(0.93)	(6.39)	(-0.82)
γ_η	0.58		0.64
t-stat.	(3.07)		(3.52)
γ_w		-0.07	-0.22
t-stat.		(-0.40)	(-2.05)
$\bar{R}^2$	64.11	-0.78	66.82
Crit. Value	(40.90)	(40.28)	(53.93)

Panel D: $K = 8$

	Model 1	Model 2	Model 3
γ_0	0.32	1.54	-0.07
t-stat.	1.58	4.19	-0.26
γ_η	0.54		0.60
t-stat.	3.13		3.75
γ_w		-0.11	-0.19
t-stat.	-0.94	-2.05	
$\bar{R}^2$	60.82	1.88	62.59
Crit. Value	(36.51)	(34.71)	(49.94)

Table 5: Cross-Sectional Pricing Errors

Table 5 presents pricing errors, u_i, from cross-sectional regressions of average returns on exposure to consumption level innovation risk exposure,

$$\bar{R}_i - \bar{R}_f = \gamma_0 + \gamma_\eta \beta_{i,\eta},$$

where $\bar{R}_i$ is the average real quarterly return on a set of 55 portfolios formed on asset growth, book-to-market ratio, market value, past 12-month return, net stock issues, and total accruals, and R_f is the real quarterly compounded return on a Treasury Bill closest to one month to maturity. The independent variable $\beta_{i,\eta}$ is the slope coefficient from the first stage regression,

$$\prod_{j=0}^{8} R_{i,t-j} = a_i + \beta_{i,\eta} \sum_{j=0}^{7} \hat{\eta}_{t-j} + e_{i,t},$$

where $\hat{\eta}_{t+1}$ is the innovation in the level of consumption growth. In addition to pricing errors, we present the mean absolute error (*m.a.e.*) and the results of a χ^2_{N-1} test that the residuals are jointly equal to zero. Data are sampled at the quarterly frequency over the period September, 1953 through December, 2012.

Decile	AG	BM	MV	P12	SI	TA
1	0.22	-0.21	-0.31	-1.44	-0.03	-0.28
2	0.67	0.14	-0.30	-1.69	-0.16	-0.16
3	0.61	0.58	0.18	-1.00	-0.17	0.07
4	0.21	0.39	-0.12	0.00	-0.19	0.11
5	0.38	0.21	-0.13	0.11	-0.46	0.46
6	0.04	0.06	0.10	0.30		0.67
7	-0.44	-0.20	0.07	0.52		-0.16
8	0.00	0.37	0.37	0.54		-0.43
9	-0.08	0.59	0.49	0.18		-0.71
10	-0.24	0.58	-0.23	0.07		-0.17
m.a.e.: 0.34						
H_0: $\mathbf{u}_i = 0$ 0.64 (0.65)						

Table 6: Relation Between Portfolio Betas and Characteristics

Table 6 presents results of regressions of portfolio betas on characteristics,

$$\left(\hat{\beta}_{it} - \bar{\beta}_t\right) = d_{0t} + \mathbf{d}_t \left(\mathbf{X}_{it} - \bar{X}_t\right) + v_{it},$$

where $\hat{\beta}_{it}$ is the portfolio exposure to cumulative consumption level risk estimated using data from time 0 through time t and $\mathbf{X}_{it}$ is a vector of portfolio characteristics at time t. The characteristics are those used to form portfolios; asset growth (AG), book-to-market ratio (BM), market value (MV), past 12 month return (P12), stock issuance (SI), and total accruals (TA). The table reports mean estimates $\bar{\mathbf{d}}_t$ and t-statistics calculated as in Fama and MacBeth (1973). Data are sampled at the quarterly frequency over the period September, 1953 through December, 2012.

	AG	BM	MV	$P12$	SI	TA	$\bar{R}^2$
Mean	0.57	0.02	-0.48	1.71	-1.66	-5.97	59.47
t-stat.	9.96	1.16	-76.16	35.79	-24.14	-47.56	

Table 7: Implied Firm-Level Betas

Table 7 depicts summary statistics for portfolios sorted on betas predicted by portfolio-level regressions of betas on characteristics. Each month t, using data available to month t, we regress cross-sectionally demeaned estimated exposures of 55 portfolios sorted on asset growth, book-to-market ratio, market value, past 12 month return, stock issuance, and total accruals onto their cross-sectionally de-meaned characteristics for the month. We utilize the portfolio level regression coefficients to construct firm-level betas, and repeat the procedure each month from September, 1983 through November, 2012. We then form portfolios on quintiles of calculated betas for monthly holding periods. Panel A presents regressions of firm returns on estimated betas,

$$r_{i,t+1} = \gamma_{0,t} + \gamma_{\eta,t}\tilde{\beta}_{i,\eta,t} + u_{i,t},$$

where $\tilde{\beta}_{i,t}$ is the calculated risk exposure. We report mean parameter estimates and t-statistics calculated as in Fama and MacBeth (1973). Panel B presents means, *ex ante* betas, and *ex post* betas for value-weighted portfolios formed on quintiles of calculated risk exposure. The *ex post* betas are estimated via the regression

$$\prod_{j=0}^{3} R_{p,t-j} = a_p + \beta_{\eta,p} \sum_{j=0}^{3} \eta_{t-j} + e_{p,t}.$$

In Panel C, we report means, *ex ante* betas, and *ex post* betas for equally-weighted portfolios formed on quintiles of calculated risk exposures. Data cover the period June, 1984 through December 2012. Mean returns are nominal and calculated using monthly returns; risk exposures are calculated using quarterly returns and deflated to real using the PCE deflator from the BEA.

Panel A: Fama-MacBeth Regressions

	$\bar{\gamma}_0$	$\bar{\gamma}_\eta$
Mean	0.565	0.221
t-stat	(1.463)	(3.782)

Panel B: Value-Weighted Portfolios

Quintile	Mean	Ex ante β_η	Ex post β_η
1	0.925	1.155	4.079
2	1.080	2.494	4.373
3	1.212	3.219	5.748
4	1.444	3.936	7.581
5	1.318	5.130	6.686

Panel C: Equally-Weighted Portfolios

Quintile	Mean	Ex ante β_η	Ex post β_η
1	0.867	1.268	1.112
2	1.058	2.566	1.731
3	1.193	3.269	2.734
4	1.350	3.993	3.159
5	1.777	5.296	5.003

Table 8: Factor Model Risk Adjustment

Table 8 presents time series regressions of returns on consumption beta-sorted quintile portfolios on factors from the Fama and French (2014) and Hou, Xue, and Zhang (2014) factor models:

$$\begin{aligned} R_{p,t+1} - R_f &= \alpha_p^{FF} + \beta_{p,MRP} R_{MRP,t+1} + \beta_{p,SMB} R_{SMB,t+1} + \beta_{p,HML} R_{HML,t+1} \\ &\quad + \beta_{p,CMA} R_{CMA,t+1} + \beta_{p,RMW} R_{RMW,t+1} + \epsilon_{p,t+1}^{FF} \\ R_{p,t+1} - R_f &= \alpha_p^{HXZ} + \beta_{p,MKT} R_{MKT,t+1} + \beta_{p,ME} R_{ME,t+1} + \beta_{p,IA} R_{IA,t+1} \\ &\quad + \beta_{p,ROE} R_{ROE,t+1} + \epsilon_{p,t+1}^{HXZ}. \end{aligned}$$

Panel A presents results for the Fama and French (2014) model and Panel B results for the Hou, Xue, and Zhang (2014) model. Data are sampled at the monthly frequency from June, 1984 through December, 2012.

Panel A: Fama-French (2014) Model

Quintile		α	β_{MRP}	β_{SMB}	β_{HML}	β_{CMA}	β_{RMW}	R^2
1	Coefficient	-0.28	1.21	-0.38	0.02	-0.07	-0.07	90.89
	t-stat	-2.38	49.42	-8.61	0.27	-0.81	-1.21	
2	Coefficient	-0.19	1.12	-0.28	-0.01	0.11	0.22	96.44
	t-stat	-3.04	85.78	-11.91	-0.35	2.28	7.22	
3	Coefficient	-0.04	1.04	-0.01	0.01	0.11	0.30	96.55
	t-stat	-0.62	84.85	-0.64	0.33	2.45	10.49	
4	Coefficient	0.15	0.97	0.21	0.03	0.16	0.21	96.01
	t-stat	2.45	73.45	8.71	0.88	3.32	6.89	
5	Coefficient	0.65	0.92	0.36	-0.04	0.25	-0.01	91.86
	t-stat	6.52	44.51	9.63	-0.80	3.36	-0.13	
5-1	Coefficient	0.93	-0.29	0.75	-0.06	0.32	0.06	34.48
	t-stat	4.77	-7.06	10.12	-0.57	2.21	0.67	

Panel B: Hou, Xue, and Zhang (2014) Model

Quintile		α	β_{MKT}	β_{ME}	β_{IA}	β_{ROE}	R^2
1	Coefficient	0.14	1.08	0.31	0.03	-0.57	82.64
	t-stat	0.88	29.08	6.13	0.37	-9.49	
2	Coefficient	0.09	1.01	0.50	0.23	-0.27	91.38
	t-stat	0.96	45.21	16.28	4.66	-7.38	
3	Coefficient	0.23	0.90	0.66	0.22	-0.21	91.21
	t-stat	2.48	41.90	22.41	4.80	-6.02	
4	Coefficient	0.47	0.81	0.76	0.21	-0.27	88.20
	t-stat	4.38	32.41	22.25	3.82	-6.68	
5	Coefficient	1.05	0.76	0.85	0.08	-0.42	81.94
	t-stat	7.15	22.32	18.26	1.09	-7.68	
5-1	Coefficient	0.91	-0.32	0.54	0.05	0.15	24.82
	t-stat	4.40	-6.74	8.22	0.49	1.92	

Table 9: Industry Risk Exposures

Table 9 presents mean returns, betas, and standard deviations of betas for industry group portfolios. Industry groups are defined according to Global Industrial Classification Standard Codes (GICS) obtained from Compustat. Betas are computed using portfolio-level relations between risk exposures and characteristics. Results of Fama and MacBeth (1973) regressions of returns on betas are presented in Panel B,

$$R_{p,t+1} = \gamma_{0,t} + \gamma_{\eta,t}\beta_{p,t} + u_t,$$

where we report averages of the point estimates of $\gamma_{0,t}$ and $\gamma_{1,t}$ and associated standard errors. Data are sampled at the monthly frequency over the period June, 1984 through December, 2012.

Panel A: Summary Statistics

Industry	$\bar{R}$	β_η	σ_{β_η}	Industry	$\bar{R}$	β_η	σ_{β_η}
Energy	1.19	3.34	0.55	Household Products	1.30	3.39	0.44
Materials	1.17	3.22	0.43	Healthcare	1.30	3.32	0.47
Capital Goods	1.15	3.41	0.36	Pharmaceuticals	1.70	2.87	0.48
Commercial Services	0.96	3.55	0.43	Banks	1.16	2.94	0.70
Transportation	1.14	3.33	0.38	Diversified Financials	1.18	3.12	0.42
Automobiles and Components	0.96	3.13	0.51	Insurance	1.17	2.89	0.42
Consumer Durables	0.92	3.50	0.51	Real Estate	0.80	3.54	0.45
Consumer Services	0.95	3.61	0.40	Software	1.38	3.41	0.44
Media	1.07	3.35	0.58	Technology Hardware	1.25	3.46	0.49
Retailing	1.00	3.34	0.50	Semiconductors	1.73	3.11	0.61
Food and Staples Retail	1.06	3.11	0.38	Telecommunications	1.34	2.83	0.72
Food, Beverage, and Tobacco	1.08	3.13	0.37	Utilities	1.04	2.76	0.46

Panel B: Fama-MacBeth Regressions

	$\bar{\gamma}_0$	$\bar{\gamma}_\eta$
Mean	-0.190	0.456
t-stat	-0.263	2.052

Table 10: Decomposition of Industry Risk Exposures

Table 10 decomposes industry risk exposures into proportions arising from industry characteristics,

$$
\begin{aligned}
1 &= \frac{Var\left(\bar{\beta}_t\right)}{Var\left(\beta_{p,t}\right)} + \frac{Var\left(\delta_{AG,t}AG_{p,t}\right)}{Var\left(\beta_{p,t}\right)} + \frac{Var\left(\delta_{BM,t}BM_{p,t}\right)}{Var\left(\beta_{p,t}\right)} + \frac{Var\left(\delta_{MV,t}MV_{p,t}\right)}{Var\left(\beta_{p,t}\right)} \\
&+ \frac{Var\left(\delta_{P12,t}P12_{p,t}\right)}{Var\left(\beta_{p,t}\right)} + \frac{Var\left(\delta_{SI,t}SI_{p,t}\right)}{Var\left(\beta_{p,t}\right)} + \frac{Var\left(\delta_{TA,t}TA_{p,t}\right)}{Var\left(\beta_{p,t}\right)} + \frac{P_{p,t}}{Var\left(\beta_{p,t}\right)},
\end{aligned}
$$

where $AG_{p,t}$, $BM_{p,t}$, $MV_{p,t}$, $P12_{p,t}$, $SI_{p,t}$, and $TA_{p,t}$ are the demeaned average portfolio asset growth, book-to-market ratio, market value, past 12-month return, stock issuance, and total accruals, respectively, $\bar{\beta}_t$ is the cross-sectional mean risk exposure at time t and $P_{p,t}$ represent covariance terms. Data are sampled for 24 industry groups over the period June, 1984 through December, 2014.

Industry	$\bar{\beta}$	AG	BM	MV	P12	SI	TA	Corr.
Energy	0.496	0.038	0.009	0.190	0.481	0.096	0.053	-0.363
Materials	0.793	0.010	0.017	0.044	0.180	0.017	0.015	-0.077
Capital Goods	1.164	0.011	0.012	0.025	0.104	0.028	0.038	-0.383
Commercial Services	0.804	0.003	0.008	0.037	0.073	0.035	0.015	0.025
Transportation	1.031	0.006	0.028	0.026	0.125	0.052	0.060	-0.328
Automobiles and Components	0.573	0.008	0.015	0.065	0.308	0.040	0.066	-0.075
Consumer Durables	0.587	0.005	0.023	0.022	0.159	0.022	0.045	0.138
Consumer Services	0.918	0.010	0.006	0.049	0.177	0.038	0.048	-0.245
Media	0.443	0.016	0.014	0.039	0.141	0.032	0.038	0.278
Retailing	0.605	0.002	0.007	0.082	0.142	0.026	0.052	0.085
Food and Staples Retail	1.025	0.009	0.006	0.157	0.287	0.099	0.055	-0.637
Food, Beverage, and Tobacco	1.106	0.005	0.004	0.182	0.216	0.072	0.018	-0.604
Household Products	0.757	0.013	0.018	0.086	0.204	0.051	0.029	-0.158
Healthcare	0.677	0.076	0.025	0.059	0.105	0.040	0.019	0.000
Pharmaceuticals	0.642	0.034	0.142	0.106	0.353	0.210	0.044	-0.531
Banks	0.306	0.004	0.022	0.117	0.172	0.044	0.020	0.316
Diversified Financials	0.848	0.011	0.005	0.102	0.079	0.039	0.070	-0.154
Insurance	0.846	0.013	0.060	0.043	0.183	0.072	0.052	-0.269
Real Estate	0.743	0.016	0.036	0.062	0.287	0.090	0.058	-0.293
Software	0.770	0.020	0.059	0.071	0.349	0.033	0.053	-0.355
Technology Hardware	0.618	0.010	0.007	0.046	0.198	0.011	0.053	0.058
Semiconductors	0.397	0.023	0.023	0.117	0.412	0.014	0.048	-0.033
Telecommunications	0.290	0.010	0.007	0.121	0.191	0.088	0.055	0.239
Utilities	0.722	0.008	0.035	0.219	0.294	0.049	0.017	-0.345

Table 11: Summary Statistics of Industry Risk Premia

Table 11 presents means and standard deviations of industry risk premier. The first two columns are means and standard deviations assuming a constant price of consumption risk, $\gamma_\eta = 0.58$, as estimated in Table 4. The second set of columns utilize risk premia calculated using a time varying price of consumption risk. The price of consumption risk is estimated from an expanding window regression of characteristics portfolio returns on risk exposures. Ex ante betas are computed using the relation between characteristics and characteristic portfolio-level betas. Data are sampled at the quarterly frequency over the period July, 1984 through December, 2012.

	Constant		Time-Varying	
Industry	Mean	Std.	Mean	Std.
Energy	1.934	0.313	1.732	0.396
Materials	1.859	0.251	1.666	0.351
Capital Goods	1.974	0.207	1.764	0.306
Commercial Services	2.053	0.250	1.835	0.339
Transportation	1.926	0.218	1.724	0.318
Automobiles and Components	1.809	0.293	1.620	0.377
Consumer Durables	2.025	0.291	1.815	0.395
Consumer Services	2.084	0.232	1.864	0.329
Media	1.935	0.333	1.736	0.422
Retailing	1.931	0.287	1.731	0.378
Food and Staples Retail	1.795	0.218	1.606	0.305
Food, Beverage, and Tobacco	1.811	0.211	1.619	0.298
Household Products	1.961	0.255	1.752	0.321
Healthcare	1.916	0.271	1.714	0.333
Pharmaceuticals	1.657	0.275	1.485	0.330
Banks	1.697	0.397	1.528	0.461
Diversified Financials	1.802	0.241	1.613	0.320
Insurance	1.671	0.239	1.495	0.314
Real Estate	2.046	0.249	1.832	0.345
Software	1.969	0.254	1.761	0.329
Technology Hardware	1.998	0.284	1.787	0.360
Semiconductors	1.801	0.351	1.609	0.391
Telecommunications	1.635	0.413	1.476	0.479
Utilities	1.595	0.259	1.431	0.335

Table 12: Relation of Industry Risk Premia to Economic Environment

Table 12 presents results of regressions of *ex ante* industry risk premia on an indicator variable and consumption growth,

$$rp_{p,t} = a_p + d_p I_{recession,t} + c_p \Delta c_t + v_{p,t},$$

where $rp_{p,t} = \bar{\hat{\beta}}_{p,t}\gamma_{\eta,t}$ is industry p's average risk premium over a calendar quarter, $I_{recession,t}$ is an indicator variable that takes the value one if the economy is in NBER recession during the quarter t and zero otherwise. Risk premia are calculated using *ex ante* betas and prices of risk, $\gamma_{\eta,t}$, estimated from an expanding window regression of characteristics portfolio returns on risk exposures. Ex ante betas are computed using the relation between characteristics and characteristic portfolio-level betas. The table presents point estimates of the coefficients and associated t-statistics. Data are sampled at the quarterly frequency over the period July, 1984 through December, 2012.

Industry	d_p	c_p	t_d	t_c
Banks	-0.38	-40.19	-2.29	-3.13
Telecommunications	-0.46	-31.49	-2.70	-2.35
Insurance	-0.38	-30.03	-3.44	-3.51
Consumer Durables	-0.49	-26.58	-3.55	-2.44
Media	-0.53	-25.90	-3.58	-2.23
Household Products	-0.33	-24.36	-2.91	-2.72
Technology Hardware	-0.45	-24.00	-3.51	-2.42
Utilities	-0.24	-23.30	-1.98	-2.46
Healthcare	-0.27	-21.99	-2.21	-2.34
Pharmaceuticals	-0.24	-21.20	-1.97	-2.27
Retailing	-0.47	-20.99	-3.55	-2.02
Semiconductors	-0.39	-20.61	-2.80	-1.88
Transportation	-0.36	-20.56	-3.22	-2.33
Software	-0.41	-19.54	-3.51	-2.15
Diversified Financials	-0.44	-17.75	-3.96	-2.04
Automobiles and Components	-0.33	-16.89	-2.43	-1.58
Materials	-0.35	-15.96	-2.78	-1.62
Capital Goods	-0.34	-15.95	-3.17	-1.87
Commercial Services	-0.34	-14.95	-2.77	-1.57
Food, Beverage, and Tobacco	-0.22	-14.90	-2.04	-1.76
Food and Staples Retail	-0.34	-14.15	-3.18	-1.67
Energy	-0.29	-12.41	-2.01	-1.10
Consumer Services	-0.35	-12.22	-2.94	-1.33
Real Estate	-0.36	-9.52	-2.90	-0.99

Figure 1: Cross-Sectional Fit

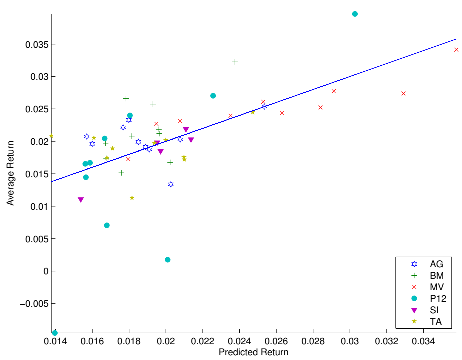
Figure 1 presents the fit of cross-sectional regressions of average returns on risk exposures,

$$\bar{R}_i - R_f = \gamma_0 + \gamma_\eta \beta_{i,\eta} + u_i,$$

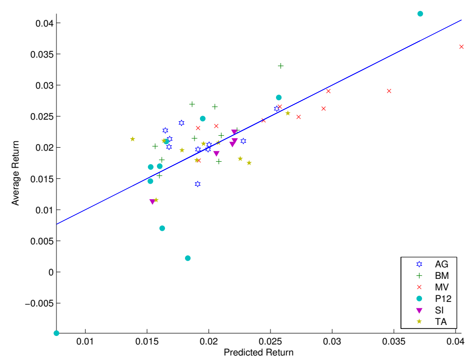
where risk exposures, $\beta_{i,\eta}$ are estimated from the first stage regression,

$$\prod_{j=0}^{K-1} R_{i,t-j} \quad = \quad a_i + \beta_{i,\eta} \sum_{j=0}^{7} \hat{\eta}_{t-j} + \beta_{i,w} \sum_{j=0}^{K} \hat{w}_{t+1} + e_{i,t},$$

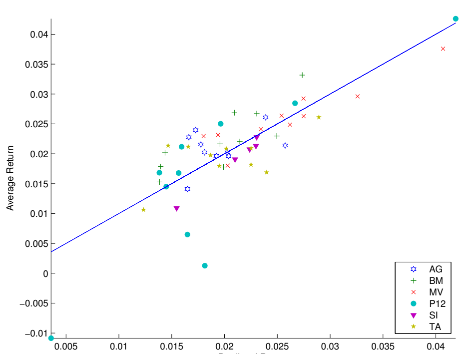
for varying lag lengths, K, where η_{t-j} is the innovation in log real per capita consumption growth at time $t-j$. Panels (a)-(d) present results using lag lengths $K = 1, 2, 4, 8$. Returns are returns to 55 portfolios sorted on asset growth (AG), book-to-market ratio (BM), market capitalization (MV), past 12-month return (P12), stock issuance (SI), and total accruals (TA). Individual scatter points represent the loci of predicted expected return and average expected return. The solid blue line is the 45-degree line. Data cover the period September, 1953 through December, 2012 and are sampled at the quarterly frequency.



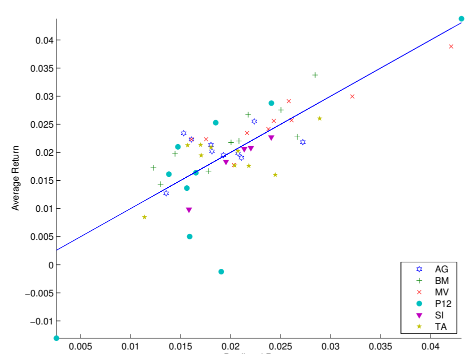
(a) $K = 1$



(b) $K = 2$



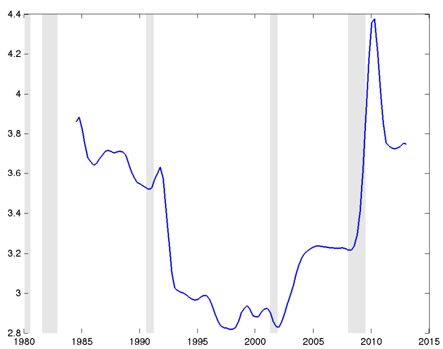
(c) $K = 4$



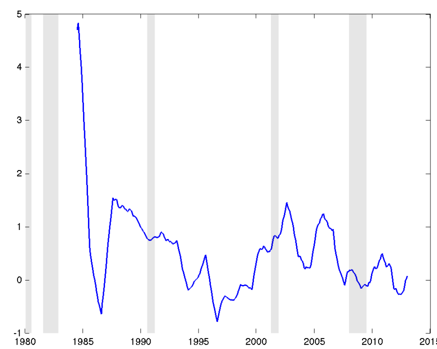
(d) $K = 8$

Figure 2: Loadings of Betas on Characteristics

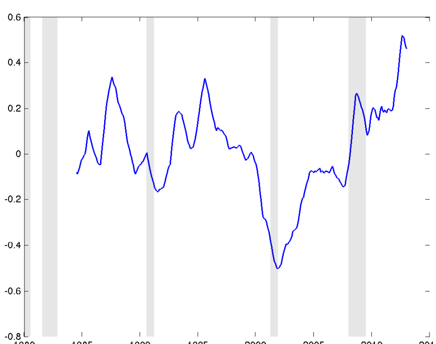
Figure 2 depicts the loadings of cross-sectionally demeaned estimated betas on cross-sectionally demeaned characteristics over time. Betas are estimated by regressing cumulative returns over four quarters on cumulated consumption growth over four quarters using an expanding window starting with the time period September, 1953 through June, 1983. We depict the mean beta over time in subfigure (a). Time series of loadings are depicted for (b) asset growth, (c) book-to-market ratio, (d) market value, (e) past 12-month return, (f) stock issuance, and (g) total accruals. NBER recessions are depicted as grey bars. Coefficients are smoothed over the past 12 months by averaging.



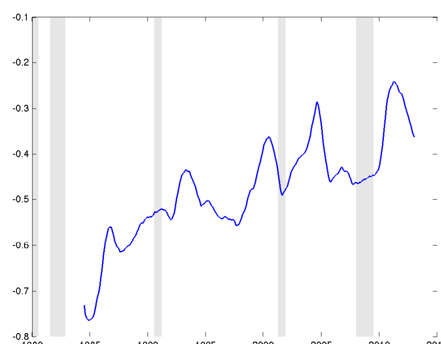
(a) Mean



(b) Asset Growth

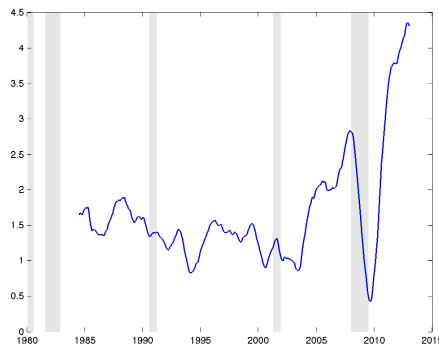


(c) Book-to-Market

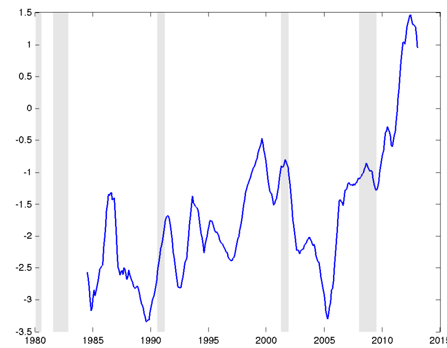


(d) Market Value

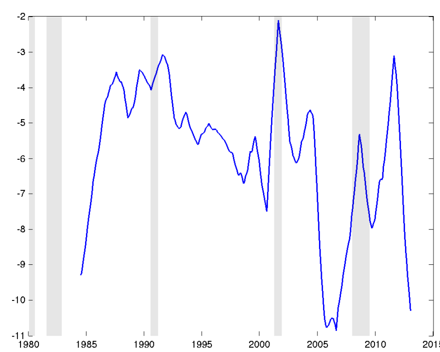
Figure continued on next page.



(e) Past 12 Month Return



(f) Stock Issuance



(g) Total Accruals

Figure 3: Time Series of *ex ante* Betas

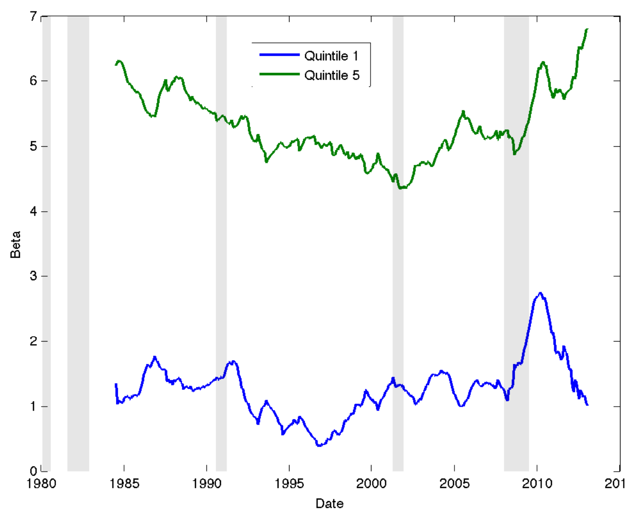
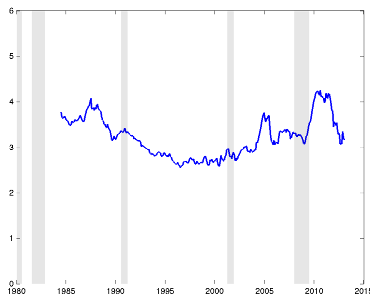
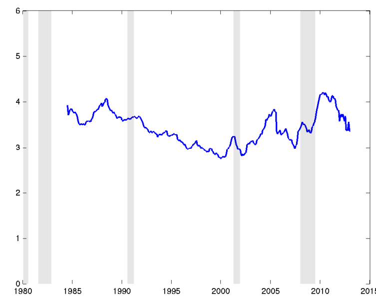


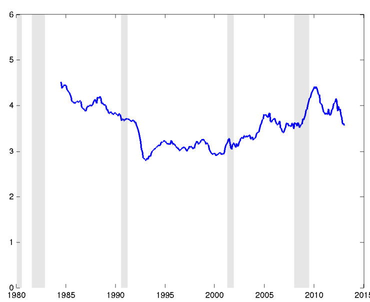
Figure 4: Industry Betas



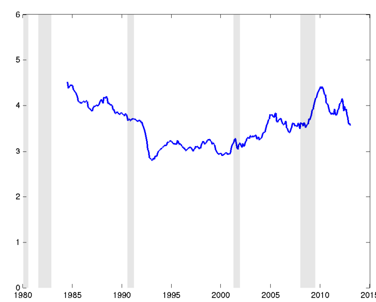
(a) Energy



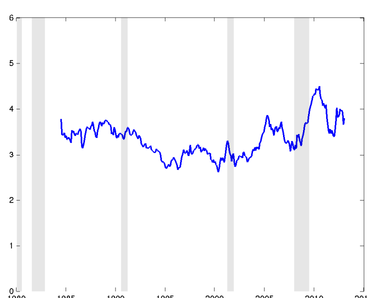
(b) Materials



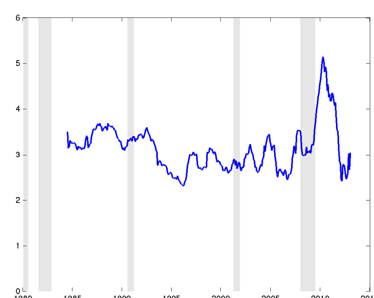
(c) Capital Goods



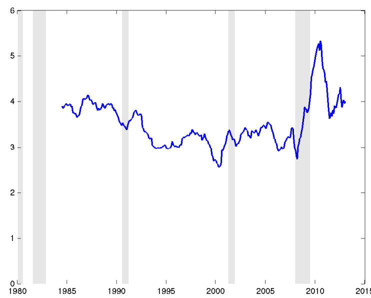
(d) Commercial Services



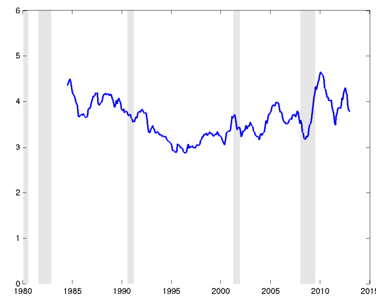
(e) Transport



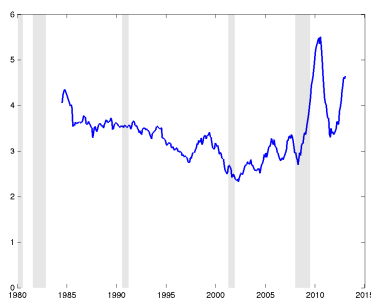
(f) Autos



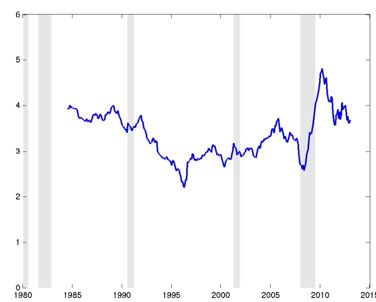
(g) Consumer Durables



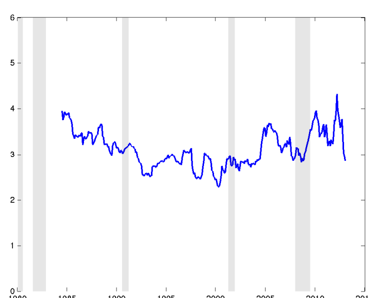
(h) Consumer Services



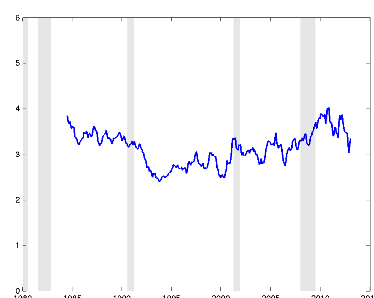
(i) Media



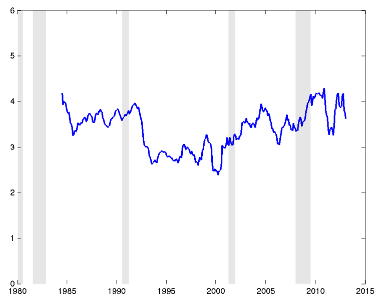
(j) Retailing



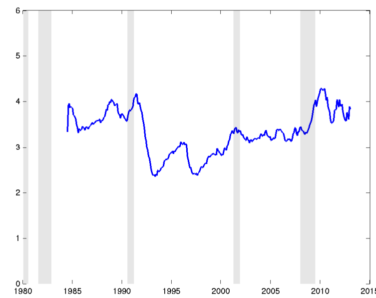
(k) Food & Staples Retail



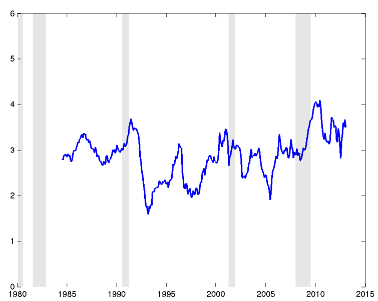
(l) Food, Beverage, and Tobacco



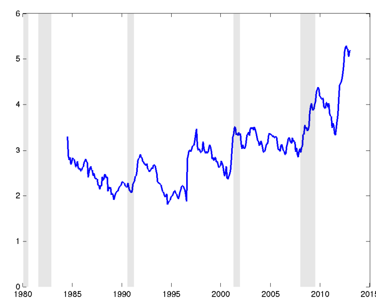
(m) Household Products



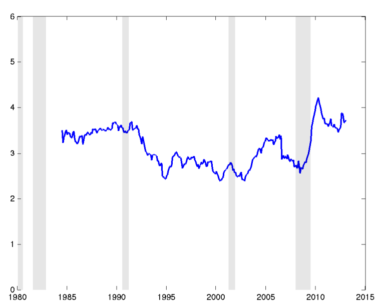
(n) Healthcare



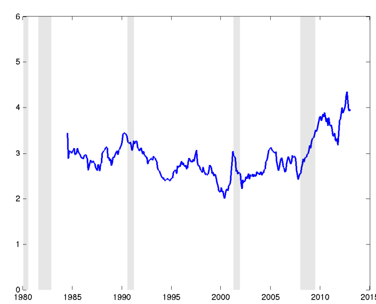
(o) Pharmaceuticals



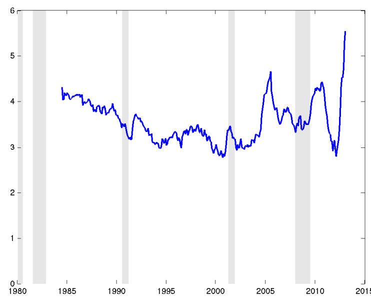
(p) Banks



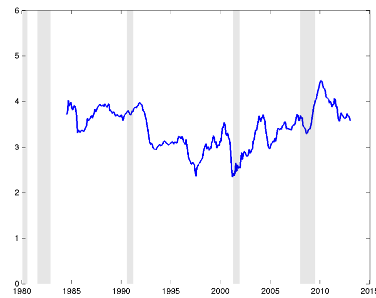
(q) Diversified Financials



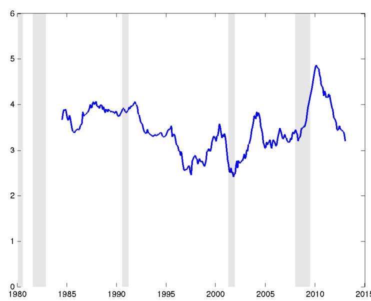
(r) Insurance



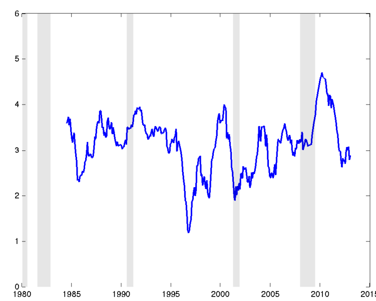
(s) Real Estate



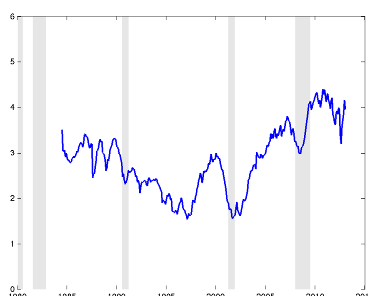
(t) Software



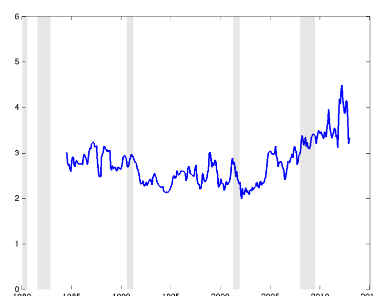
(u) Technology Hardware



(v) Semiconductors



(w) Telecommunications



(x) Utilities

Figure 5: Price of Consumption Risk