# Firm Characteristics, Consumption Risk, and Firm-Level Risk Exposures☆

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## Abstract

We propose a novel approach to measuring firm-level risk exposures and costs of equity. Using a simple consumption-based asset pricing model that explains nearly two-thirds of the variation in average returns across 55 anomaly portfolios, we map the relation between exposures to consumption risk and portfolio-level characteristics. We use this relation to calculate exposures to consumption risk at the firm level and show that the calculated consumption risk exposures yield portfolios with large differences in average returns and *ex post* consumption risk exposures consistent with those predicted by our calculated betas. Further, industry betas and risk premia implied by our procedure display economically intuitive variation over time. Finally, Fama-MacBeth regressions suggest that risk exposures calculated using our procedure dominate those from alternative factor models at explaining cross-sectional variation in returns.

*Keywords:*
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## 1. Introduction

In the past fifteen years, consumption-based asset pricing (Lucas (1978) and Breeden (1979)) 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 regarding consumption-based models' ability to capture *cross-sectional* variation in average returns has resulted in a new interest

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in understanding the links between consumption growth and asset prices.[1]

Given the recent empirical success of consumption-based pricing models in explaining cross-sectional variation in returns, one might expect 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 those presented in (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 between *ad hoc* statistical factor models and 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-frequency consumption risk. This difficulty is particularly pronounced at a more disaggregated level, especially at the level of the firm where practical risk adjustments are often required. 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 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 the exposure to consumption risk. Because consumption data is observed only at low frequencies, and because recessions drive macroeconomic risk exposure but are infrequent, it is probable that direct estimates of firm-level return exposure to consumption risk will be difficult to obtain.

In this paper, we propose a methodology to address these problems. First, building on Bansal et al. (2005), we posit a simple reduced-form model in which the relevant priced risk is the innovation to consumption growth. They demonstrate the importance of low-frequency (co-)variation in detecting consumption risk; specifically, they project portfolio-level cash flow growth rates onto a moving-average of consumption growth and find that this approach can explain average return variation across size, value, and momentum portfolios. Unlike that paper, we test (and later employ) the model on a large set of anomaly 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 a much larger set of anomaly portfolios. However, while we view the

[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 et al. (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 et al. (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.

contribution to the anomalies literature as quite important, we view a central contribution of the paper as providing a bridge between the recent innovations in the consumption-based asset pricing literature with the often vexing measurement of the cost of capital necessary for many applications in finance.

To operationalize this, we consider the possibility of a measurable link between firm characteristics and consumption risk exposures. Our method follows the suggestion of production-based asset pricing models, such as Zhang (2005), that imply that risk exposures are related to characteristics, perhaps through the composition of the return to a firm's optimal investment level. These risk exposures, in turn, should relate to the covariance of a firm's returns with some source of aggregate priced risk. At the aggregated portfolio level described above, where it may be easier to detect low-frequency consumption risk, we show that consumption risk exposures are related to the very characteristics that govern the formation of the anomaly portfolios. Then, we employ the portfolio-level mapping between low-frequency consumption risk and these characteristics to infer firm-level dynamic consumption risk exposures (given a set of point-in-time measured firm characteristics). In sum, we build on the idea that consumption risk exposures may be better measured by focusing on low-frequency co-variation in Bansal et al. (2005), extending their finding to a far larger set of anomaly portfolios that also facilitates a rich risk exposure to characteristic mapping. Further, by mapping these exposures to measured characteristics, our novel method then yields a real-time, consumption-based cost of capital estimate that facilitates both a time-varying consumption risk exposure as well as a level of disaggregation (industry- or firm-level) uncommon in the traditional consumption-based asset pricing literature.

In order to assess whether the procedure correctly sorts firms based on consumption risk exposures, we form portfolios on the basis of *ex ante* exposure to consumption risk using firm characteristics measured at the time of the portfolio formation. 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 75 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 et al. (2014).

To highlight the applicability of our approach, we estimate 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 result in a negative and statistically insignificant risk premium, Fama and MacBeth (1973) regressions of returns on consumption risk exposures suggest a positive and statistically significant risk premium. We also show that the time-series variation in industry risk exposures do suggest countercyclical risk premia.

Finally, we examine the performance of our measured consumption exposures in understanding both cross-sectional and time series variation in risk premia. In Fama and MacBeth (1973) *firm-level* regressions, our consumption risk exposure has highly statistically significant power for explaining cross-sectional variation in returns. In contrast, the risk exposures to the factors in Fama and French (2014) five-factor model have little statistical power, which may be a symptom of the difficulty in estimating (time-invariant) firm-level risk exposures.

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. Further, we estimate risk exposures and analyze cross-sectional regressions of portfolio mean returns on risk measures. Section 3 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 4, and an application to firm cost of capital is discussed in Section 5. We make concluding remarks in Section 6.

## 2. Consumption Risk Premia in Average Returns

Our particular interest in this paper is in bridging the gap between the measurement of the cost of capital necessary for many applications in finance and the renaissance of models of the stochastic discount factor that are functions of risks buried in aggregate consumption growth. In particular, we have in mind a model in the vein of the canonical Lucas (1978) asset pricing model, which states that an asset's price is determined by its conditional covariance with a representative agent's intertemporal marginal rate of substitution (IMRS). In the cross-section, such a model implies that the risk premium on any asset $i$ can be expressed as

$$E\left[R_{i,t+1} - R_{f,t}\right] = \lambda\beta_i, \tag{1}$$

where $\beta_i = Cov\left(r_{i,t+1}, \eta_{t+1}\right)/Var\left(\eta_{t+1}\right)$ is the coefficient from regressing returns on the unexpected shock to consumption growth, denoted by $\eta_{t+1}$, and $\lambda$ is the market price of consumption growth risk. This expression suggests that cross-sectional variation in risk premia will be determined by assets' return exposures to shocks to consumption growth, yet early empirical failures of this modeling framework left it largely sidelined with respect to practical applications. We build on more recent successes in measuring consumption risk; specifically Bansal et al. (2005) demonstrate the success of low-frequency consumption risk in explaining the cross-sectional variation in size, value, and momentum portfolios (see also Parker and Julliard (2005), Hansen et al. (2008), and Bansal et al. (2009) for related arguments concerning the importance of measuring low-frequency consumption risk exposures).

A goal of our paper is to then identify a mapping between measured consumption risk exposures (that successfully describe the cross-section of expected returns) and characteristics. In order to do so, we consider two aspects of a set of assets on which to test the fit of the model. First, the set of assets should span a wide variety of characteristics in order to provide as much cross-sectional information as possible for our mapping. Here, we consider a large set of anomaly portfolios (significantly expanding the set of anomalies that the measurement of low-frequency consumption risk must address relative to the portfolios employed in Bansal et al. (2005)). Second, if the model cannot describe cross-sectional returns related to a particular empirically relevant characteristic, it is unlikely that the mapping between characteristics and risk exposures will be useful. These two considerations guide our choice of test assets.

### *2.1. Testing Portfolios*

We estimate consumption risk exposures and cross-sectional risk premium in equation (1) using a set of anomaly portfolios sorted on characteristics. 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 et al. (2010) due to the ease of fitting a model to their two-factor structure. Harvey et al. (2014) catalog 316 variables that have been found to have significant power to forecast cross-sectional variation in returns, and Green et al. (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 to the question 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).[3] 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).[4] 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. 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 2012.

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

[3]We follow the existing literature in constructing these variables. Details can be found in Davis et al. (2000) for the book-to-market ratio and market capitalization, Fama and French (1996) for past 12-month returns, Pontiff and Woodgate (2008) for stock issuance, Cooper et al. (2008) for asset growth, and Sloan (1996) for accruals.

[4]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 et al. (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. Results in this paper including a set of profitability-sorted portfolios are available from the authors upon request.

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.

*2.2. Estimating Risk Exposures*

The key input to our analysis is a measure of the exposure of asset returns to consumption risk, encapsulated in the consumption beta in equation (1). Building on Bansal et al. (2005), we estimate risk exposures by regressing cumulated portfolio returns on cumulated innovations in (log) consumption growth.[5]

$$\prod_{j=0}^{K-1} R_{i,t-j} \quad = \quad a_i + \beta_i \sum_{j=0}^{K-1} \hat{\eta}_{t-j} + e_{i,t}, \tag{2}$$

for different windows $K$, where $R_{i,t-j}$ is the gross real return on portfolio $i$. The innovation, $\hat{\eta}_{t-j}$ is simply the difference in (log) consumption growth in quarter $t - j$ and its unconditional mean. Consumption is measured as per capita real personal consumption expenditures on nondurable goods and services. Data throughout the paper are converted to real using the personal consumption expenditure deflator. Data are obtained from the National Income and Product Account tables at the Bureau of Economic Analysis at the quarterly frequency from the first quarter of 1947 through the fourth quarter of 2012.

We estimate univariate versions of regression (2) to obtain risk exposures. Risk exposures for a window $K = 4$ are reported in Table 2.[6] 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 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 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 risk exposure and average returns.

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

[5]Technically, our approach differs modestly from Bansal et al. (2005) in that they employ the low-frequency covariance between portfolio dividend growth and aggregate consumption growth rates, whereas we directly measure the low-frequency exposure between portfolio total returns and consumption growth. If we instead measure consumption risk based on the dividend growth exposure for the full set of anomaly portfolios, we estimate a positive and statistically significant price of risk and the adjusted $R^2$ describing the link between cross-sectional variation in average returns and consumption risk exposures is 41.88%. While the return-based low-frequency consumption risk exposures based on total returns performs better in the cross-section (as reported below), these are qualitatively similar in that both low-frequency approaches capture a surprisingly large amount of cross-sectional variation in average returns with a simple consumption risk exposure. These results are available upon request.

[6]We report risk exposures for $K = 4$ as our later results indicate that this window produces risk exposures with the best cross-sectional fit. Risk exposures for alternative windows are available from the authors upon request.

*2.3. 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

$$\bar{R}_i - \bar{R}_f = \gamma_0 + \gamma_\eta \hat{\beta}_i + u_i, \tag{3}$$

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 $\hat{\beta}_i$ is the first stage estimates of univariate regressions of portfolio $i$'s return on the consumption innovation, $\eta_t$.

Results of the cross-sectional regressions are presented in Table 3. We present a total of four specifications. The specifications vary across the number of periods over which innovations and returns are compounded. We examine four windows, $K = 1, 2, 4, 8$. In the case of $K = 1$, we are only allowing for the contemporaneous relation between returns and consumption innovations. In the remaining versions, lower frequency covariation becomes 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 et al. (2010), who suggest that the cross-sectional $R^2$ may overstate the model fit.[7]

First, 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 innovations. 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.

Comparing columns (2)-(4), for which we vary $K = 2, 4, 8$, the results are qualitatively similar. A model with a single exposure to consumption growth risk performs surprisingly well in explaining cross-sectional variation in a large set of anomaly portfolios. The best performance of the model in terms of adjusted $R^2$ is in the case where $K = 4$. The price of consumption 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-

[7]The critical value is calculated by generating 5000 random samples with 238 time series observations of a normally distributed variable with mean zero and standard deviation $\sigma_\eta$ to match sample standard deviation of the consumption 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 $R^2$.

based model provides a good description of the cross-sectional variation in average returns of these portfolios.

The fit of the model is provided in Figure 1, and we report the magnitude of pricing errors in Table 4. 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 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 $\chi^2$ 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.[8]

## 3. Using Characteristics to Estimate Risk Exposures

### *3.1. Mapping Characteristics into Risk Exposures*

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 those embodied in the market portfolio. This intuition is formalized in the context of an investment-based asset pricing model in Zhang (2005), where he argues that high book-to-market firms earn a larger risk premium than low book-to-market firms because the book-to-market ratio represents a proxy for a firm's exposure to risk. This point is made more explicit in Lin and Zhang (2013), who forcefully argue that characteristics and risk factor covariances represent two sides of the same coin.[9]

While we do not write down a formal production-based asset pricing model, we nevertheless assume that the relation between an asset's consumption risk exposure and a set of relevant characteristics can be captured by projecting the risk exposure onto the set of characteristics. Specifically, we assume that

$$\beta_{i,t} = f\left(\mathbf{X}_{i,t}, \boldsymbol{\delta}\right) + \xi_{i,t}, \tag{4}$$

where $\beta_{i,t}$ is the time $t$ consumption risk exposure of asset $i$'s return, $\mathbf{X}_{i,t}$ is a set of relevant characteristics, and $\boldsymbol{\delta}$ is a set of coefficients that describe this link.

[8] 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 et al. (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 et al. (2014). These results are available from the authors upon request.

[9] 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 et al. (2008) and Li et al. (2009)), accruals (Wu et al. (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 et al. (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.

With the previous section's evidence that a set of low-frequency consumption risk exposures fits the cross-section of average returns well, we next turn to investigating the relation between consumption risk exposures and measured characteristics. As discussed, 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, we assume (as a plausible starting point) that there is a linear relation between portfolio risk exposures and characteristics,

$$\left(\hat{\beta}_{p,t} - \bar{\beta}_t\right) = \delta_0 + \boldsymbol{\delta}\left(\mathbf{X}_{p,t} - \bar{X}_t\right) + v_{p,t} \tag{5}$$

where $\hat{\beta}_{p,t}$ is the portfolio exposure to cumulative consumption risk estimated using data from time 0 through time $t$ and $\mathbf{X}_{p,t}$ is a vector of portfolio characteristics at time $t$. Thus, risk exposures are allowed to vary over time due to changing characteristics, $\mathbf{X}_{p,t}$. We cross-sectionally de-mean variables to remove any time trends that might generate spurious time variation in risk exposures.

We estimate the coefficients $\boldsymbol{\delta}$ using portfolio level estimated risk exposures and characteristics, where the risk exposure, $\hat{\beta}_{p,t}$, is estimated using only consumption and return data available at time $t$. That is, we begin by estimating the portfolio risk exposures using returns and consumption growth from December, 1954 through June, 1983, and expand the window of estimation through December, 2012, yielding a panel of 119 quarters of risk exposures for 55 portfolios.

In order to get some sense of how the characteristics and risk exposures relate to one another, we present the panel regression coefficients, $\hat{\boldsymbol{\delta}}$, their associated standard errors, and regression adjusted $R^2$ in Table 5. The coefficients on characteristics generally conform with the results of the cross-sectional regressions. The past 12-month return is positively related to risk exposures, while market value, stock issuance, and total accruals are negatively related to risk exposures. Asset growth and the book-to-market ratio are somewhat confounding, as the former is negatively and the latter positively related to average returns. All of the point estimates are statistically significantly different than zero. Finally, the characteristics explain a substantial portion of the panel variation in risk exposures, with an adjusted $R^2$ of 55.67%.

### *3.2. 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

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

where $i$ indexes firms, $p$ represents portfolios, and $\omega_i$ is the weight on asset $i$ in the portfolio. Consequently, by estimating the coefficients $\boldsymbol{\delta}$ at the portfolio level, we can use the coefficients to retrieve firm-specific risk measures at the firm level.[10] This translation between the portfolio

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

and the firm level relations of risk exposures and characteristics is similar to the use of portfolio-level 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. We use firm-level characteristics to form portfolios that are characterized by differences in *ex ante* consumption risk exposure. Specifically, each month $t$, we calculate a consumption growth innovation exposure for every firm, using the panel regression coefficients $\boldsymbol{\delta}$ and firm characteristics known at time $t$.[11] 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 6, Panel A, 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 across the five quintiles, ranging from 88 basis points per month in the first quintile to 136 basis points in the fifth quintile. This increasing relation is consistent with the cross-sectional results indicating a positive relation between consumption risk exposure and average returns. Additionally, *ex post* risk exposures are generally increasing across quintiles, rising from 3.66 for the first quintile to 6.20 for the fifth quintile. However, the risk exposures depart from monotonicity in the fourth quintile, with an *ex post* $\beta$ of 6.64. The magnitudes of the *ex post* risk exposures are similar to, but generally greater than those predicted *ex ante*. The results suggest that in value-weighted portfolios that our procedure generally replicates the increasing expected returns and *ex post* risk exposures that we expect.

In Panel B of Table 6, we present mean returns, the *ex ante* beta, and the *ex post* beta for five equally-weighted portfolios. Similar to the results in Panel A, 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 75 basis points per month, and the difference is statistically significantly different than zero ($t$-statistic=3.07). 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 2. For brevity, we present betas for equally-weighted portfolios; results for value-

[11] In addition to the procedure discussed here, we also considered a fully real-time version by calculating firm-level betas using *only* information available at time $t$. The procedure replaces the panel regression, equation (5), with quarter-by quarter regressions of risk measures on characteristics,

$$\left(\hat{\beta}_{p,t} - \bar{\beta}_t\right) = \delta_{0,t} + \boldsymbol{\delta}_t \left(\mathbf{X}_{p,t} - \bar{X}_t\right) + v_{p,t},$$

to obtain a time series of risk exposures and mappings between risk exposures and characteristics. The coefficients are smoothed over 12 months, and applied to time $t$ firm-level characteristics to generate a firm-level beta. An advantage to this approach is that it uses only information available at time $t$ to form portfolios, rather than coefficients $\boldsymbol{\delta}$ estimated over the full span of the data. However, time variation in the mapping between risk exposures and characteristics is difficult to justify theoretically. We present results of this approach, which are qualitatively similar to those presented in the paper, in an online appendix.

weighted portfolios are similar. The fifth quintile beta is relatively high in the 1980s, but drops in the 1990s, with a gradual increase into the mid-2000s. The beta jumps substantially in 2008-2009, before moderating slightly in 2011 and 2012. The first quintile beta exhibits a similar pattern, but with a more pronounced and uninterrupted increase in the 2000s. Our general impression is that when economic conditions deteriorate, as in the late 1980s, late 1990s, and late 2000s, the betas tend to increase, whereas when economic conditions improve, as in the late to mid 1990s and mid 2000s, the betas decline, suggesting that time-series variation in the betas likely comes from a common source. The extreme quintile betas are 80% 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 and time-series variation in consumption risk exposures.

In principle, the procedure that we outline in this section could be used to retrieve firm-level risk exposures relative to *any* risk factor that might explain cross-sectional variation in returns. However, we speculate that it is important that the portfolio risk exposures are strongly related to the characteristics meant to instrument for the risk exposures. To investigate this idea, we repeat our procedure using standard market (CAPM) betas, that is betas with respect to the value-weighted CRSP index. As with our consumption betas, we regress returns on the 55 characteristic-sorted portfolios from time 0 to time $t$ on the index, and estimate a panel regression using the time series of risk exposures and characteristics for the portfolios. We use the coefficients from this regression to form firm-level risk exposures, and sort firms into quintiles on the basis of these predicted exposures. We hold firms in portfolios from month $t$ to $t + 1$, and repeat the procedure through the end of our data sample.

Summary statistics for portfolios formed in this manner are presented in Table 7. As in Table 6, we report means of value- and equally-weighted portfolio returns sorted on the predicted market beta, the portfolio predicted market beta, and the actual market beta exposures of the portfolio returns. The table shows that there is a modest, but weak increasing pattern in mean returns for both value- and equally-weighted portfolio returns, but the magnitude is small compared to our preferred method and the pattern is far from monotonic. By construction, *ex ante* market betas increase from 0.93 to 1.12 in the case of value-weighted portfolios, and from 0.93 to 1.13 for equally-weighted portfolios. In value-weighted portfolios, the *ex-post* measured risk exposures are generally increasing; market betas increase from 0.95 for the second quintile to 1.17 for the fifth quintile. Equally-weighted *ex post* market betas exhibit a U-shape, with first quintile market betas of 1.28 and fifth quintile market betas of 1.26. Thus, the results indicate that while there is some relation between *ex ante* market betas measured using our procedure and the actual market betas of the portfolios, the relationship is somewhat modest.

The reason behind these weaker results using market betas rather than the consumption betas is the lack of a strong relationship between market betas and measured characteristics. The $R^2$ from our panel regression of market betas on characteristics is 13.5%, compared to 55.7% for the consumption betas. This result indicates that, in contrast to our results for consumption betas, characteristics provide limited information about market betas and highlights the idea that for the procedure that we outline in this paper to be successful, the portfolio-level risk exposures must be strongly related to portfolio-level characteristics for resulting firm-level characteristics to generate consistent *ex-post* risk exposures.

### *3.3. 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 factor risks. Fama and French (2014) and Hou et al. (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:

$$\begin{aligned} R_{p,t+1} - R_f &= \alpha_p^{FF} + \beta_{p,MRP} R_{MRP,t+1} + \beta_{p,SMB} R_{SMB,t+1} \\ &\quad + \beta_{p,HML} R_{HML,t+1} + \beta_{p,CMA} R_{CMA,t+1} \\ &\quad + \beta_{p,RMW} R_{RMW,t+1} + \epsilon_{p,t+1}^{FF} \qquad (6) \\ R_{p,t+1} - R_f &= \alpha_p^{HXZ} + \beta_{p,MKT} R_{MKT,t+1} + \beta_{p,ME} R_{ME,t+1} \\ &\quad + \beta_{p,IA} R_{IA,t+1} + \beta_{p,ROE} R_{ROE,t+1} \\ &\quad + \epsilon_{p,t+1}^{HXZ}, \qquad (7) \end{aligned}$$

where the first model is proposed in Fama and French (2014) and the second in Hou et al. (2014).[12]

The Fama and French (2014) five-factor model draws on evidence from Novy-Marx (2013) and Aharoni et al. (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).[13] Hou et al. (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 et al. (2014).[14]

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 et al. (2014) model. We use the equally-weighted characteristic beta portfolios and equally-weighted portfolios to form the Fama and French (2014) factors.[15] 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 three quintiles are negative and those of the top two quintiles are positive. The difference in extreme quintile intercepts is 76 basis points per month, statistically significantly different than zero at less than the 1% critical level

[12] In untabulated results, we augment each model with the momentum factor from Carhart (1997). Results are qualitatively similar. Results are available from the authors upon request.

[13] Data are obtained from Kenneth French's website at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. Thanks to Ken French for making these data available.

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

[15] The Hou et al. (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.

($t$-statistic=3.64). 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 from 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 portfolios 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 et al. (2014) four-factor model are similar. Intercepts are increasing across quintiles, with a statistically significant premium of 73 basis points for high consumption beta portfolios in excess of low consumption beta portfolios ($t$-statistic=3.19). 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 79% 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 et al. (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 factor models remain based on factors motivated by statistical considerations, 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.

## 4. Industry Costs of Capital

As an application of our methodology, we investigate costs of capital for firms grouped on their primary industrial classification. 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 quite difficult to estimate. 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 equally-weighted portfolios on the basis of industry groups, and examine *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 173 basis points per month for Semiconductors. It is not immediately apparent, however, that these large average returns represent compensation for average consumption risk exposure. The average consumption beta of the semiconductor industry, 3.18, is slightly lower than that of the 3.50 beta of the real estate industry. In unreported results, we regress average returns on the average betas and find a statistically insignificant negative relation between average returns and risk exposures. As in Fama and French (1997), unconditional risk exposures do not seem to capture differences in average returns across industry groups.

The negative relation between average returns and average risk exposures may reflect temporal variation in consumption betas and compensation for consumption risk exposure. As shown in the table, consumption betas are volatile. The Capital Goods industry has the least volatile risk exposure, with a standard deviation that is approximately 10% of its mean. In contrast, the Banks and Telecommunications industry groups have risk exposure volatilities that are approximately 20% of their means. Cross-sectionally, different industries display vastly different variation in the exposure of their returns to risks in consumption growth. In Panel B, we show that accounting for this variation by use of Fama and MacBeth (1973) regressions of real quarterly returns on *ex ante* betas results in a positive and statistically significant price of consumption risk exposure. This evidence reinforces to the danger of assuming constant risk exposures in evaluating industry expected returns.

As a point of comparison, we also tabulate standard market betas, obtained from regressing returns on industry portfolios on the return on the CRSP equally-weighted index. Betas are estimated using 60-month rolling windows; we tabulate the average of these betas in Table 9. As shown in the table, these market beta averages are substantially different from the *ex ante* betas from our procedure; the correlation between the two is approximately 0.40. In Panel B, we repeat the Fama and MacBeth (1973) regressions for the market betas. The results indicate that while the point estimate for the price of market beta risk is positive, averaging 0.235, this average is not statistically significantly different than zero.

Given the fact that time variation in consumption betas is important, it is natural to ask from what sources is the variation derived? We examine "variance decompositions" of industries' risk exposures by evaluating the role for the various industry-level characteristics that are driving our consumption beta construction:

$$\begin{aligned} Var\left(\beta_{p,t}\right) &= Var\left(\bar{\beta}_t\right) + Var\left(\delta_{AG} AG_{p,t}\right) \\ &\quad + Var\left(\delta_{BM} BM_{p,t}\right) + Var\left(\delta_{MV} MV_{p,t}\right) \\ &\quad + Var\left(\delta_{P12} P12_{p,t}\right) + Var\left(\delta_{SI} SI_{p,t}\right) \\ &\quad + Var\left(\delta_{TA,t} TA_{p,t}\right) + P_{p,t}, \end{aligned} \tag{8}$$

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.

The table 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 82.4% and accounting for between 42% of variation for Telecommunications and Banks, and 133% for Capital Goods. This may be interpreted as an important period fixed effect shared by all industries (that itself varies significantly with the business cycle). The second most important determinant is the past 12-month return, accounting for an average of 15.5% of variation, and ranging from driving 4.0% of Commercial Services beta variation to 34.9% of Semiconductors beta variation. Other characteristics are also important, including market size and equity issuance. A closer examination yields one key takeaway – our methodology uncovers the importance of a number of different industry (or firm) characteristics to fully map out the variation in consumption beta through time.

Finally, we examine implied costs of capital for industry portfolios. We allow both the consumption risk exposure to vary over time and use the point estimate with $K = 4$ from Table 3 of $\hat{\gamma} = 0.58$. Averages and standard deviations of annualized risk premia are presented in Table 11. As shown in the table, costs of capital vary substantially over time and across industries. The lowest risk premium in the table is for the Utilities industry group, averaging 5.72% per annum and the highest is for the Consumer Services industry group, with an average of 7.46% per annum. The most volatile risk premia are exhibited by the Telecommunications and Banks industry groups, and the most stable by the Food, Beverage, and Tobacco, Food and Staples, and Capital Goods industry groups. Our impression from the table is that industry groups that are usually thought of as having relatively stable revenues and earnings, such as those in the Consumer Staples sector (Food and Staples Retail and Food, Beverage, and Tobacco) have relatively low averages and volatilities of risk premia. In contrast, industries in which revenues and earnings are more cyclical, such as Consumer Services, Consumer Durables, and Commercial Services, have higher average risk premia.

Finally, we plot the time series of a select group of industry risk premia in Figure 3. We choose the Energy, Automobiles and Components, Consumer Durables, Food, Beverage, and Tobacco, Banks, and Semiconductors industry groups due to potential differences in exposure to macroeconomic risk and volatility of cash flows. All six industry groups exhibit substantial sensitivity to the impact of the financial crisis in 2008-2010, with risk premia attaining their maxima for each industry group during this period. The reaction to the crisis is more muted in some groups than others; in the Food, Beverage, and Tobacco industry group, risk premia rise by approximately 4% to about 10% per annum, while risk premia in the Automobiles and Components and Consumer Durables industry groups rise about 8% to nearly 14% per annum. All risk premia fall in the wake of the financial crisis, but remain elevated relative to historical levels.

## 5. Firm Costs of Capital

In the final part of this paper, we use our methodology to examine *firm-level* costs of capital implied by the framework in this paper. Since we do not know true costs of capital, it is difficult to assess whether our model performs "better" than alternatives at measuring these objects. We conduct Fama and MacBeth (1973) firm-level regressions using our framework and alternative models. While indirect, this analysis at least provides insight into whether our model performs as well or better at capturing significant cross-sectional variation in returns.[16]

As described above, we first compute consumption beta exposures for all stocks in the CRSP universe with information on the characteristics used in our sample and CRSP share codes 10 and 11. We also compute firm-level risk exposures to the five Fama and French (2014) risk factors, $MRP$, $SMB$, $HML$, $RMW$, and $CMA$, using rolling regressions over the past 60-month window relative to return measurement. Data on the factors are obtained from Kenneth French's website as above. We then perform month-by-month cross-sectional regressions as in Fama and MacBeth (1973),

$$\begin{aligned} R_{i,t+1} = \quad & \gamma_{0,t} + \gamma_{\eta,t}\beta_t + \gamma_{MRP,t}\beta_{MRP,t} + \gamma_{SMB,t}\beta_{SMB,t} \\ & + \gamma_{HML,t}\beta_{HML,t} + \gamma_{RMW,t}\beta_{RMW,t} \\ & + \gamma_{CMA,t}\beta_{CMA,t} + u_{i,t+1}. \end{aligned} \tag{9}$$

In Table 12, we report averages of the prices of risk, $\bar{\gamma}_k$, $k = \{\eta, MRP, SMB, HML, RMW, CMA\}$ and associated $t$-statistics. Data are sampled at the monthly frequency and cover the period June, 1984 through December, 2012.

In the first row of the table, we present results for a restricted version of equation (9) where we restrict all prices of risk except $\gamma_{\eta,t}$ to be equal to zero, representing the univariate performance of the betas estimated using our methodology. As shown in the table, the consumption beta bears a positive average price of risk, $\bar{\gamma}_\eta = 0.191$, which is highly statistically significantly different than zero as indicated by the $t$-statistic of 2.783. The implied average risk premium is remarkably similar to that obtained in portfolio-level cross-sectional regression. The coefficient implies an average quarterly risk premium of 0.57 compared to the point estimate of 0.58 reported in Table 4.

In the second and third rows of the table, we present estimates from restricted regressions corresponding to the CAPM and the Fama and French (2014) five-factor model. The table indicates that risk exposures associated with these factors perform poorly in terms of statistical significance at capturing cross-sectional variation in returns. The average point estimate for the

[16] In the Internet Appendix, we also analyze costs of capital implied by our model for the constituents of the Dow 30 Industrial Average as of December, 2012. From these analyses, we conclude that our procedure produces firm-level risk premia that seem largely consistent with intuition. Namely, risk premia vary substantially over time and correlate with economic and financial market conditions. Our methodology permits the measurement of these risk premia and their variation, bridging firm-level quantities of interest to consumption-based asset pricing.

market beta, $\bar{\gamma}_{MRP}$ is positive, with a point estimate of 0.007, but not statistically distinguishable from zero with a standard error of 0.042. The estimated average price of risk is similar in multiple regression, with an average point estimate of 0.099, which remains statistically insignificant with a standard error of 0.674. The remaining factors do not fare much better. The factors $SMB$, $HML$, $CMA$, and $RMW$ are not statistically significantly different than zero. Only $HML$ approaches marginal significance, with a $t$-statistic of 1.766.

In the final two rows of the table, we present estimates of prices of risk for the CAPM and the five-factor model, augmented by our consumption beta. Results are qualitatively similar to those shown above. The consumption beta maintains a positive and statistically significant average price of risk in both specifications, with average point estimates that are not economically materially different than those reported in the univariate regression. None of the remaining factors bears a statistically significant price of risk. Thus, the results indicate that our measure of consumption beta bears a positive and statistically significant risk price that is robust to alternative risk adjustments.

The statistical significance of our consumption beta and insignificance of the remaining risk exposures suggest that point estimates of periodic regression coefficients are much more stable for the consumption beta than for the return factor betas. One possible reason for this result is the difficulty in estimating firm-level risk exposures discussed above. The statistical significance of our consumption beta suggests that there is some stable cross-sectional variation in returns that can be captured by the consumption risk exposures. However, if there is stable cross-sectional variation related to the return factor exposures, this variation is being obscured by measurement error in the exposures or volatility in the exposures themselves.

## 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. In this paper, we propose an approach to bridge this gap.

We suggest 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 have average returns that are consistent with theoretical predictions, and risk exposures that are ex post consistent with the ex ante predictions of our framework. This evidence suggests that our framework performs well at capturing cross-sectional variation in consumption risk exposures.

We also examine the implications of risk measures and risk premia implied by our procedure for industries and individual firms. Our results indicate that our calculated risk measures describe a significant degree of the variation in average returns both across industries and firms. The risk exposures also perform better than risk exposures implied by leading return factor models at explaining cross-sectional variation in returns. Our results also indicate that there is substantial variation in risk premia over time, and that this variation differs substantially across firms. In particular, risk premia appear to be more stable for firms in less cyclically exposed industries such as consumer staples, and more variable in industries such as financials.

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 anomaly 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 innovations,

$$\prod_{j=0}^{3} R_{i,t-j} \quad = \quad a_i + \beta_i \sum_{j=0}^{3} \hat{\eta}_{t-j} + e_{i,t},$$

where $\hat{\eta}_t$ is the innovation in 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, $\beta_i$, 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: Cross-Sectional Regressions

Table 3 presents estimates of cross-sectional regressions of average excess portfolio returns on risk measures,

$$\bar{R}_i - \bar{R}_f = \gamma_0 + \gamma_\eta \beta_i + u_i,$$

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 variable, $\beta_i$, is the slope coefficient from the first stage regression,

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

where $\hat{\eta}_{t+1}$ is the innovation in of consumption growth. Results are presented for cumulations over $K = 1, 2, 4, 8$ periods. 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.

| | $K = 1$ | $K = 2$ | $K = 4$ | $K = 8$ |
|---|---|---|---|---|
| $\gamma_0$ | 0.51 | 0.19 | 0.19 | 0.32 |
| $t$-stat. | (1.88) | (0.80) | (0.93) | (1.58) |
| $\gamma_\eta$ | 0.44 | 0.54 | 0.58 | 0.54 |
| $t$-stat. | (2.01) | (2.71) | (3.07) | (3.13) |
| $\bar{R}^2$ | 38.20 | 56.63 | 64.11 | 60.82 |
| Crit. Value | (43.07) | (44.34) | (40.90) | (36.51) |

Table 4: Cross-Sectional Pricing Errors

Table 4 presents pricing errors, $u_i$, from cross-sectional regressions of average returns on exposure to consumption innovation risk exposure,

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

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 variable, $\beta_i$, is the slope coefficient from the first stage regression,

$$\prod_{j=0}^{3} R_{i,t-j} \quad = \quad a_i + \beta_i \sum_{j=0}^{3} \hat{\eta}_{t-j} + e_{i,t},$$

where $\hat{\eta}_{t+1}$ is the innovation in consumption growth. In addition to pricing errors, we present the mean absolute error (*m.a.e.*) and the results of a $\chi^2_{N-1}$ 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 5: Relation Between Portfolio Betas and Characteristics

Table 5 presents results of panel regressions of portfolio betas on characteristics,

$$\left(\hat{\beta}_{p,t} - \bar{\beta}_t\right) = \delta_0 + \delta\left(\mathbf{X}_{p,t} - \bar{X}_t\right) + v_{p,t}$$

where $\hat{\beta}_{p,t}$ is the portfolio exposure to cumulative consumption risk estimated using data from time 0 through time $t$ and $\mathbf{X}_{p,t}$ 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 estimates $\hat{\delta}$ and associated $t$-statistics. Data are sampled at the quarterly frequency over the period September, 1953 through December, 2012.

| | $AG$ | $BM$ | $MV$ | $P12$ | $SI$ | $TA$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|
| Estimate | 0.24 | -0.12 | -0.45 | 1.19 | -1.00 | -5.05 | 55.67 |
| $t$-stat. | 4.99 | -9.60 | -132.63 | 48.55 | -18.53 | -39.83 | |

Table 6: Implied Firm-Level Betas

Table 6 depicts summary statistics for portfolios sorted on betas predicted by portfolio-level regressions of betas on characteristics. We estimate a panel regression of 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 on their cross-sectionally de-meaned characteristics. 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 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

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

In Panel B 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: Value-Weighted Portfolios

| Quintile | Mean | Ex ante $\beta$ | Ex post $\beta$ |
|---|---|---|---|
| 1 | 0.884 | 1.339 | 3.663 |
| 2 | 1.139 | 2.616 | 4.351 |
| 3 | 1.210 | 3.216 | 5.815 |
| 4 | 1.317 | 3.815 | 6.642 |
| 5 | 1.362 | 4.801 | 6.202 |

Panel B: Equally-Weighted Portfolios

| Quintile | Mean | Ex ante $\beta$ | Ex post $\beta$ |
|---|---|---|---|
| 1 | 0.900 | 1.693 | -0.886 |
| 2 | 1.030 | 2.673 | 0.410 |
| 3 | 1.086 | 3.256 | 2.278 |
| 4 | 1.258 | 3.862 | 3.273 |
| 5 | 1.649 | 4.922 | 5.027 |

Table 7: Implied Firm-Level Market Betas

Table 7 depicts summary statistics for portfolios sorted on betas predicted by portfolio-level regressions of market betas on characteristics. We estimate a panel regression of 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 on their cross-sectionally de-meaned characteristics. 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 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

$$R_{p,t} = a_p + \beta_{m,p} R_{m,t} + e_{p,t},$$

where $R_{m,t}$ is the excess return on the value-weighted market portfolio. In Panel B 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.

Panel A: Value-Weighted Portfolios

| Quintile | Mean | Ex ante $\beta_m$ | Ex post $\beta_m$ |
|---|---|---|---|
| 1 | 0.840 | 0.929 | 0.949 |
| 2 | 0.910 | 0.995 | 0.961 |
| 3 | 1.034 | 1.028 | 0.981 |
| 4 | 0.989 | 1.059 | 1.016 |
| 5 | 0.946 | 1.119 | 1.166 |

Panel B: Equally-Weighted Portfolios

| Quintile | Mean | Ex ante $\beta_m$ | Ex post $\beta_m$ |
|---|---|---|---|
| 1 | 0.987 | 0.928 | 1.282 |
| 2 | 1.178 | 0.997 | 1.071 |
| 3 | 1.216 | 1.029 | 1.040 |
| 4 | 1.237 | 1.060 | 1.034 |
| 5 | 1.220 | 1.134 | 1.256 |

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 et al. (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 et al. (2014) model. Data are sampled at the monthly frequency from June, 1984 through December, 2012.

Panel A: Fama-French (2014) Model

| Quintile | | $\alpha$ | $\beta_{MRP}$ | $\beta_{SMB}$ | $\beta_{HML}$ | $\beta_{CMA}$ | $\beta_{RMW}$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| 1 | Coefficient | -0.15 | 1.24 | -0.50 | 0.17 | -0.23 | -0.18 | 90.14 |
| | t-stat | -1.23 | 47.97 | -10.56 | 2.43 | -2.48 | -2.90 | |
| 2 | Coefficient | -0.17 | 1.12 | -0.27 | -0.01 | 0.10 | 0.23 | 96.15 |
| | t-stat | 2.56 | 82.28 | -10.78 | -0.20 | 2.08 | 7.17 | |
| 3 | Coefficient | -0.13 | 1.06 | -0.01 | -0.01 | 0.17 | 0.32 | 96.32 |
| | t-stat | -2.08 | 82.03 | -0.22 | -0.21 | 3.62 | 10.59 | |
| 4 | Coefficient | 0.14 | 0.95 | 0.21 | -0.04 | 0.21 | 0.25 | 95.87 |
| | t-stat | 2.21 | 71.67 | 8.60 | -1.28 | 4.41 | 8.16 | |
| 5 | Coefficient | 0.60 | 0.89 | 0.45 | -0.10 | 0.30 | 0.03 | 91.54 |
| | t-stat | 5.94 | 41.84 | 11.75 | -1.85 | 3.95 | 0.63 | |
| 5-1 | Coefficient | 0.76 | -0.35 | 0.95 | -0.27 | 0.53 | 0.21 | 41.76 |
| | t-stat | 3.64 | -8.04 | 12.02 | -2.35 | 3.41 | 2.03 | |

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

| Quintile | | $\alpha$ | $\beta_{MKT}$ | $\beta_{ME}$ | $\beta_{IA}$ | $\beta_{ROE}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| 1 | Coefficient | 0.29 | 1.10 | 0.21 | 0.02 | -0.65 | 82.51 |
| | t-stat | 1.77 | 29.10 | 4.07 | 0.27 | -10.50 | |
| 2 | Coefficient | 0.12 | 1.01 | 0.52 | 0.21 | -0.26 | 91.25 |
| | t-stat | 1.22 | 44.55 | 16.69 | 4.35 | -7.17 | |
| 3 | Coefficient | 0.14 | 0.92 | 0.70 | 0.29 | -0.20 | 91.45 |
| | t-stat | 1.46 | 42.51 | 23.74 | 6.05 | -5.62 | |
| 4 | Coefficient | 0.42 | 0.80 | 0.77 | 0.20 | -0.23 | 89.21 |
| | t-stat | 4.18 | 34.31 | 23.91 | 3.85 | -5.92 | |
| 5 | Coefficient | 1.02 | 0.72 | 0.87 | 0.05 | -0.41 | 78.81 |
| | t-stat | 6.37 | 19.50 | 17.31 | 0.62 | -6.87 | |
| 5-1 | Coefficient | 0.73 | -0.38 | 0.66 | 0.03 | 0.23 | 28.49 |
| | t-stat | 3.19 | -7.16 | 9.19 | 0.24 | 2.70 | |

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. We also report average betas with respect to the equally-weighted CRSP index, $\bar{\beta}_m$, estimated from 60-month rolling regressions of the returns on the industry portfolio on the return on the index. Results of Fama and MacBeth (1973) regressions of returns on betas are presented in Panel B,

$$
\begin{aligned}
R_{p,t+1} &= \gamma_{0,\eta,t} + \gamma_{\eta,t}\beta_{p,t} + u_{p,\eta,t} \\
R_{p,t+1} &= \gamma_{0,m,t} + \gamma_{m,t}\beta_{m,t} + u_{p,m,t},
\end{aligned}
$$

where we report averages of the point estimates of $\gamma_{0,k,t}$ and $\gamma_{k,t}$ and associated $t$-statistics for $k = \{\eta, m\}$. Data are sampled at the monthly frequency over the period June, 1984 through December, 2012.

Panel A: Summary Statistics

| Industry | $\bar{R}$ | $\bar{\beta}$ | $\sigma_\beta$ | $\bar{\beta}_m$ | Industry | $\bar{R}$ | $\bar{\beta}$ | $\sigma_\beta$ | $\bar{\beta}_m$ |
|---|---|---|---|---|---|---|---|---|---|
| Energy | 1.19 | 3.30 | 0.48 | 0.89 | Household Products | 1.30 | 3.41 | 0.47 | 0.96 |
| Materials | 1.17 | 3.17 | 0.40 | 0.97 | Healthcare | 1.30 | 3.37 | 0.45 | 1.11 |
| Capital Goods | 1.15 | 3.36 | 0.34 | 0.99 | Pharmaceuticals | 1.70 | 3.07 | 0.46 | 1.51 |
| Commercial Services | 0.96 | 3.53 | 0.43 | 1.00 | Banks | 1.16 | 2.97 | 0.61 | 0.59 |
| Transportation | 1.14 | 3.27 | 0.37 | 0.98 | Diversified Financials | 1.18 | 3.06 | 0.37 | 1.09 |
| Automobiles and Components | 0.96 | 3.13 | 0.43 | 1.13 | Insurance | 1.17 | 2.82 | 0.39 | 0.64 |
| Consumer Durables | 0.92 | 3.43 | 0.45 | 1.06 | Real Estate | 0.80 | 3.50 | 0.36 | 0.85 |
| Consumer Services | 0.95 | 3.57 | 0.40 | 1.02 | Software | 1.38 | 3.45 | 0.46 | 1.53 |
| Media | 1.07 | 3.35 | 0.50 | 1.12 | Technology Hardware | 1.25 | 3.48 | 0.49 | 1.50 |
| Retailing | 1.00 | 3.27 | 0.47 | 1.15 | Semiconductors | 1.73 | 3.18 | 0.58 | 1.76 |
| Food and Staples Retail | 1.06 | 3.01 | 0.41 | 0.75 | Telecommunications | 1.34 | 2.93 | 0.61 | 1.35 |
| Food, Beverage, and Tobacco | 1.08 | 3.10 | 0.41 | 0.67 | Utilities | 1.04 | 2.69 | 0.43 | 0.34 |

Panel B: Fama-MacBeth Regressions

| | $\bar{\gamma}_0$ | $\bar{\gamma}_\eta$ | $\bar{\gamma}_m$ |
|---|---|---|---|
| Mean | -1.570 | 1.626 | |
| $t$-stat | -0.669 | 2.073 | |
| Mean | 0.976 | | 0.235 |
| $t$-stat | 4.291 | | 0.639 |

Table 10: Decomposition of Industry Risk Exposures

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

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

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, 2012.

| Industry | $\bar{\beta}$ | AG | BM | MV | P12 | SI | TA | Corr. |
|---|---|---|---|---|---|---|---|---|
| Energy | 0.687 | 0.003 | 0.003 | 0.185 | 0.348 | 0.011 | 0.038 | -0.273 |
| Materials | 0.969 | 0.001 | 0.003 | 0.038 | 0.095 | 0.006 | 0.010 | -0.121 |
| Capital Goods | 1.325 | 0.000 | 0.002 | 0.032 | 0.051 | 0.005 | 0.020 | -0.435 |
| Commercial Services | 0.830 | 0.000 | 0.002 | 0.015 | 0.040 | 0.014 | 0.010 | 0.089 |
| Transportation | 1.131 | 0.001 | 0.002 | 0.017 | 0.085 | 0.017 | 0.045 | -0.297 |
| Automobiles and Components | 0.825 | 0.001 | 0.004 | 0.054 | 0.226 | 0.016 | 0.051 | -0.177 |
| Consumer Durables | 0.775 | 0.000 | 0.001 | 0.019 | 0.102 | 0.005 | 0.041 | 0.056 |
| Consumer Services | 0.962 | 0.000 | 0.002 | 0.038 | 0.124 | 0.010 | 0.017 | -0.153 |
| Media | 0.611 | 0.001 | 0.006 | 0.063 | 0.097 | 0.025 | 0.047 | 0.150 |
| Retailing | 0.694 | 0.000 | 0.001 | 0.082 | 0.102 | 0.007 | 0.046 | 0.067 |
| Food and Staples Retail | 0.941 | 0.001 | 0.003 | 0.127 | 0.152 | 0.012 | 0.027 | -0.263 |
| Food, Beverage, and Tobacco | 0.935 | 0.001 | 0.001 | 0.068 | 0.136 | 0.005 | 0.010 | -0.156 |
| Household Products | 0.704 | 0.001 | 0.001 | 0.061 | 0.101 | 0.007 | 0.024 | 0.100 |
| Healthcare | 0.773 | 0.001 | 0.001 | 0.035 | 0.085 | 0.010 | 0.016 | 0.077 |
| Pharmaceuticals | 0.726 | 0.003 | 0.002 | 0.102 | 0.284 | 0.036 | 0.025 | -0.179 |
| Banks | 0.416 | 0.000 | 0.002 | 0.137 | 0.141 | 0.017 | 0.010 | 0.277 |
| Diversified Financials | 1.131 | 0.001 | 0.001 | 0.139 | 0.053 | 0.010 | 0.079 | -0.414 |
| Insurance | 1.045 | 0.001 | 0.004 | 0.040 | 0.145 | 0.012 | 0.044 | -0.290 |
| Real Estate | 1.180 | 0.001 | 0.004 | 0.051 | 0.186 | 0.029 | 0.074 | -0.525 |
| Software | 0.749 | 0.001 | 0.002 | 0.049 | 0.282 | 0.018 | 0.039 | -0.141 |
| Technology Hardware | 0.650 | 0.000 | 0.002 | 0.032 | 0.156 | 0.005 | 0.040 | 0.115 |
| Semiconductors | 0.461 | 0.002 | 0.003 | 0.096 | 0.349 | 0.005 | 0.050 | 0.034 |
| Telecommunications | 0.421 | 0.001 | 0.003 | 0.087 | 0.210 | 0.030 | 0.026 | 0.221 |
| Utilities | 0.827 | 0.001 | 0.002 | 0.048 | 0.180 | 0.011 | 0.015 | -0.084 |

Table 11: Summary Statistics of Industry Risk Premia

Table 11 presents means and standard deviations of industry risk premia utilizing risk premia calculated using time varying consumption risk exposures and the estimated price of consumption risk from Table 3 with $K = 4$. 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.

| Industry | Mean | Std. | Industry | Mean | Std. |
|---|---|---|---|---|---|
| Energy | 6.82 | 0.65 | Household Products | 7.05 | 0.66 |
| Materials | 6.57 | 0.62 | Healthcare | 6.96 | 0.63 |
| Capital Goods | 6.94 | 0.57 | Pharmaceuticals | 6.35 | 0.64 |
| Commercial Services | 7.30 | 0.66 | Banks | 6.15 | 0.80 |
| Transportation | 6.76 | 0.57 | Diversified Financials | 6.31 | 0.56 |
| Autos and Components | 6.48 | 0.69 | Insurance | 5.83 | 0.55 |
| Consumer Durables | 7.10 | 0.72 | Real Estate | 7.23 | 0.62 |
| Consumer Services | 7.38 | 0.64 | Software | 7.12 | 0.65 |
| Media | 6.93 | 0.74 | Technology Hardware | 7.19 | 0.71 |
| Retailing | 6.77 | 0.71 | Semiconductors | 6.57 | 0.74 |
| Food and Staples Retail | 6.22 | 0.58 | Telecommunications | 6.09 | 0.81 |
| Food, Bev, and Tobacco | 6.41 | 0.60 | Utilities | 5.55 | 0.57 |

Table 12: Firm-Level Fama-MacBeth Regressions

We estimate Fama and MacBeth (1973) regressions for individual firms. The regression is specified as

$$\begin{aligned} R_{i,t+1} = \quad & \gamma_{0,t} + \gamma_t\beta_{i,t} + \gamma_{MRP,t}\beta_{i,MRP,t} + \gamma_{SMB,t}\beta_{i,SMB,t} + \gamma_{HML,t}\beta_{i,HML,t} + \gamma_{RMW,t}\beta_{i,RMW,t}, \\ & +\gamma_{CMA,t}\beta_{i,CMA,t} + u_{i,t+1}, \end{aligned}$$

where $\beta_t$ is the consumption growth risk exposure estimated using the procedure described in this paper, and $\beta_k$, $k = \{MRP, SMB, HML, RMW, CMA\}$ are coefficients of multiple regressions of returns on the five Fama and French (2014) risk factors. The risk factors are the difference in the return on the market and a risk free asset, $MRP_t$, the difference in the return on a portfolio of small stocks and large stocks, $SMB_t$, the difference in the return on a portfolio of high book-to-market and low-book-to-market stocks, $HML_t$, the difference in the return on a portfolio of highly profitable firms minus the return on a portfolio of firms with low profitability, $RMW_t$, and the return on a portfolio of firms with low asset growth in excess of the return on a portfolio of firms with high asset growth, $CMA_t$. We report average coefficients and associated $t$-statistics following Fama and MacBeth (1973). Data are sampled at the monthly frequency over the period June, 1984 through December, 2012.

| | $\gamma_\eta$ | $\gamma_{MRP}$ | $\gamma_{SMB}$ | $\gamma_{HML}$ | $\gamma_{RMW}$ | $\gamma_{CMA}$ |
|---|---|---|---|---|---|---|
| Coeff. | 0.191 | | | | | |
| t-stat | 2.783 | | | | | |
| Coeff. | | 0.007 | | | | |
| t-stat | | 0.042 | | | | |
| Coeff. | | 0.046 | -0.007 | 0.176 | -0.041 | 0.045 |
| t-stat | | 0.320 | -0.091 | 1.766 | -0.553 | 0.753 |
| Coeff. | 0.219 | 0.024 | | | | |
| t-stat | 3.840 | 0.148 | | | | |
| Coeff. | 0.237 | 0.093 | -0.054 | 0.158 | -0.024 | 0.031 |
| t-stat | 5.124 | 0.702 | -0.731 | 1.656 | -0.335 | 0.541 |

Figure 1: Cross-Sectional Fit

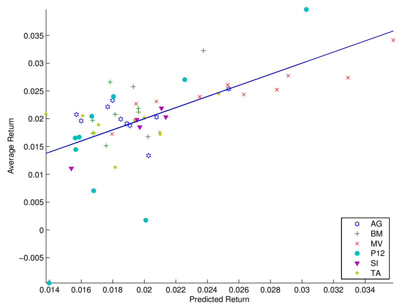
Figure 1 presents the fit of cross-sectional regressions of average returns on risk exposures,

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

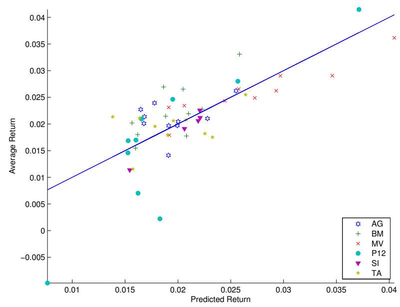
where risk exposures, $\beta_i$, are estimated from the first stage regression,

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

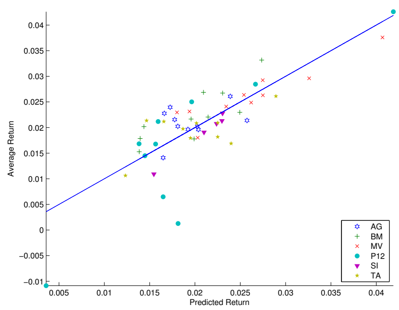
for varying lag lengths, $K$, where $\eta_{t-j}$ is the innovation in log real per capita consumption growth at time $t-j$. Panels (a)-(d) present results using lag lengths $K = 1, 2, 4, 8$. Returns are returns to 55 portfolios sorted on asset growth (AG), book-to-market ratio (BM), market capitalization (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.



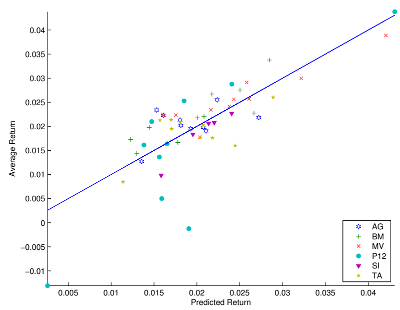

(a) $K = 1$




(b) $K = 2$




(c) $K = 4$




(d) $K = 8$

Figure 2: Time Series of ex ante Betas

Figure 2 presents the time series of ex ante betas for portfolios of firms formed on the basis of these betas. Portfolios are formed by first calculating betas using firm-level characteristics and coefficients from regressions of portfolio-level betas on portfolio-level characteristics. Each month, firms are sorted into quintiles on the basis of the calculated beta and held in a portfolio for the subsequent month. The figure presents the time series of betas for the bottom and top quintile equally-weighted portfolios over the period June, 1984 through December, 2012.

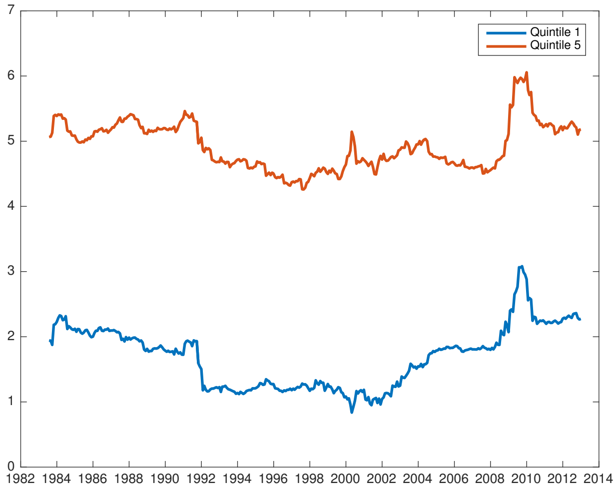
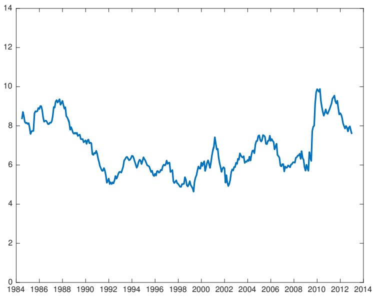
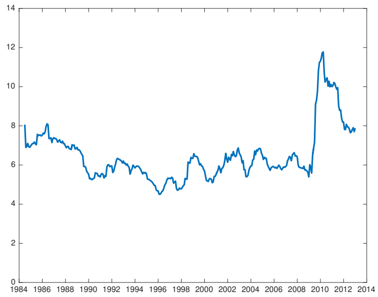


Figure 3: Industry Risk Premia

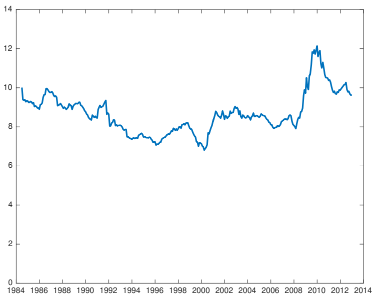
Figure 3 presents the time series of ex ante risk premia for portfolios of firms formed on the basis of GICS industry groups. Risk premia are calculated by first calculating betas using firm-level characteristics and coefficients from regressions of portfolio-level betas on portfolio-level characteristics. The resulting betas are multiplied by the annualized price of consumption risk from Table 3 with $K = 4$. Each month, firms are sorted into quintiles on the basis of GICS industry group from Compustat.



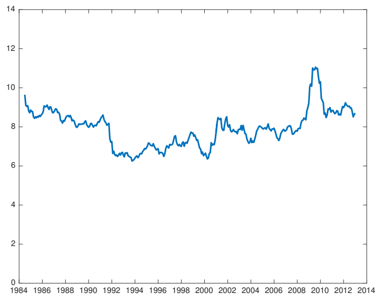

(a) Energy



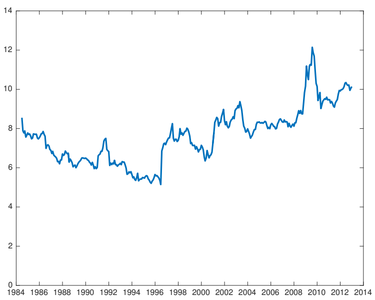

(b) Autos



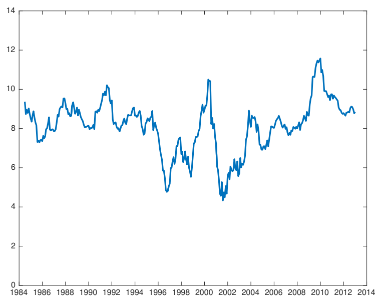

(c) Consumer Durables




(d) Food, Beverage, and Tobacco




(e) Banks




(f) Semiconductors