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Consumption Risk and Expected Futures Returns *

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Abstract

Following recent research on consumption-based asset pricing, we find that the Consumption CAPM explains up to 60 percent of the cross sectional variation in mean futures returns. The conditional version of the consumption model performs best at the quarterly horizon and outperforms both the CAPM and the Fama-French three-factor model. We show that expected futures returns can be measured by the futures' yields and that the consumption model, next to explaining mean returns, is also best at explaining the cross sectional variation in mean yields. Unlike for stock returns, ultimate consumption (i.e., contemporaneous plus future consumption) leads to lower performance of the consumption model. We conjecture that demand and supply changes lead short run consumption risk to be important for commodities, but not the long run risk.

JEL classification: G12 and G13

Keywords: futures, consumption CAPM, ultimate consumption risk

1 Introduction

Futures returns are like excess returns on assets such as stocks and bonds, whose expectations basically reflect risk premia. The determinants of futures risk premia are usually related to systematic risk based on the CAPM[1] or the Consumption CAPM (CCAPM) as in Jagannathan (1985). Although Jagannathan (1985) finds for three different agricultural futures contracts that the CCAPM implies significant risk premia and finds market prices of risk that are similar to those found in equity markets,

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[1] See, e.g., Dusak (1973), Black (1976), Carter, Rausser, and Schmitz (1983), Bessembinder (1992), and DeRoon, Nijman, and Veld (2000).

he rejects the model itself. Breeden (1980) studies a similar model on a broader class of commodity futures and finds significant consumption betas but he does not perform a full test of the asset pricing model. The evidence proclaimed so far in the empirical literature, indicates that although commodity returns appear not to be related to the movements in stock market returns[2], they do seem to be related to the changes in aggregate real consumption. The latter finding may be natural since part of the underlying commodities are strongly related to aggregate consumption itself and may be used for hedging consumption risk. Hence, the consumption-based framework seems to be a natural choice for analyzing futures returns. However, sofar no successful test of the consumption-model on futures returns has been presented.

This is related to the well-known fact that in general the CCAPM has more difficulties in explaining the cross section of stock returns than other models like the Fama-French three factor model (see Campbell and Cochrane (2000) and references therein).[3] This problem has been addressed by a stream of literature where the focus is on the underlying assumption that investors can costlessly adjust their consumption plans. For instance, Jagannathan and Wang (2005) propose that consumption and investment decisions are taken infrequently and show that the CCAPM explains more than 70 percent of the cross sectional variation in expected stock returns when consumption growth is measured from the 4th quarter of one year to the next. Also, they find that lowering the frequency of consumption growth and returns from monthly to quarterly and annual data, significantly improves the performance of the CCAPM, which is likely to result from the smaller measurement error in consumption growth at lower frequencies. Parker and Julliard (2005) conjecture that consumption may be slow to respond to stock returns, and find that *ultimate* consumption risk, defined as the covariance of a stock return and consumption growth over the quarter of the return and many following quarters, explains between 44 and 73 percent of the cross sectional variation in stock returns.

This paper follows up on these recent advances in the literature on the CCAPM by applying them to a broad cross section of 25 different futures contracts. Since these futures contracts have as the underlying assets various commodities (agriculturals, meats, energy and precious metals), as well as currencies and an equity index, this allows us to analyze the ability of the CCAPM to explain the returns on a much broader set of assets than stocks only.

[2]This is based on the unconditional version of the CAPM. However, futures contracts do exhibit systematic risk once betas are allowed to vary (Carter, Rausser and Schmitz (1983)) and when we control for SMB and HML factors (we find significant systematic risk in terms of the Fama-French three factor model in this paper).

[3]A second difficulty fo the CCAPM is that it cannot explain the time series average of stock returns, i.e., the high equity premium. In response to this, several refinements of the model have been put forward. These models focus on better ways of modelling investors preferences. For example, the model of Bansal and Yaron (2004) which uses the recursive utility preference of Epstein and Zin (1989, 1991), or Campbell and Cochrane (1999) model which allows for a habit formation in the utility specification; appear to be successful in solving these puzzles.

We find that, at the quarterly horizon, the (unconditional) CCAPM explains about 50 percent of the cross section of futures returns, whereas there is almost no explained variance at the monthly level, and an intermediate result at the yearly level. The CCAPM explains the futures returns much better than either the CAPM or Fama-French model, which account for at most 20 percent of the cross sectional variation in mean returns. When we assume that the CCAPM, CAPM and the Fama-French model hold in a conditional sense[4], allowing for time varying betas and risk premiums, the CCAPM explains up to 60 percent of the cross sectional variation in futures returns, whereas both the CAPM and the Fama-French model yield R^2s that never exceed 40 percent. Again, the CCAPM shows the best performance at the quarterly and annual frequency.

Using a simple present value relation, we show that the futures own (cash) yield is a good estimator of expected (excess) returns similar to the way dividends are estimators of expected stock returns[5]. The futures' yield has the advantage over the simple mean return that it is an ex ante measure of expected returns, whereas the mean return is an ex post measure. Using the average yield as the dependent variable in the cross-sectional regression, confirms that the CCAPM performs best at the quarterly frequency. However, the model can explain only up to 29 percent of the cross sectional variation in yields in the unconditional case and up to 36 percent in the conditional case. The Fama-French model explains the cross sectional variation in yields much better (up to 45 and 55 percent resp.), but yields negative estimates of the market risk premia.

Finally, using ultimate consumption risk, we find that the performance of the CCAPM is best using consumption growth of the contemporaneous quarter of the returns, but then deteriorates for the longer horizons. Although this contradicts the findings of Parker and Julliard (2005) for stock returns, it is consistent with the finding that the CCAPM performs best at the quarterly frequency and may be the result of supply- and demand elasticities of many of the commodities that underlie our futures contracts, inducing time-varying consumption betas. Indeed, we find that there are systematic decreases in the absolute values of the betas of our commodities w.r.t. future consumption as the horizon, over which consumption growth is measured, increases. Unlike stocks, in case of commodities demand and supply may change as a result of spot prices, making ultimate and long term consumption risk less important for our futures returns than for stock returns. This is confirmed by the pattern of consumption beta in our dataset, which indicates that the betas of futures returns with respect to consumption risk tend to fade out as the horizon over which consumption growth is measured increases. Also, the variation in commodity returns explained by production or investment growth first increases as the measurement horizon increases, and then decreases again, suggesting a lagged adjustment of production to changes in commodity prices.

[4] See Jagannathan and Wang (1996).

[5] See, e.g., Campbell and Shiller (1988) and Bekaert and Harvey (2000).

The rest of the paper is structured as follows. The next section first explains why futures yields are good estimators for expected futures returns and gives a brief outline of the unconditional and conditional CCAPM. Section 3 discusses some estimation issues and Section 4 describes the data. The empirical results are discussed in Section 5 and Section 6 concludes the paper.

2 Theory: Expected futures returns and consumption risk

2.1 Yield-based measure for expected returns

Any statistical test of asset pricing theory requires a proxy for expected returns. Traditionally, expected returns are measured as the averages of past returns. However, the estimates for the means are sensitive to the number of observations and volatility of the returns series, i.e., the estimates become less precise with shorter and more volatile series (Merton (1980)). One way to mitigate this problem, often done in empirical studies, is to group financial assets into portfolios and compute mean returns from the historical observations[6]. Alternatively, we can use another measure for expected returns that is less vulnerable. In this section we show that a present value model implies the use of convenience yields as such a measure.

To see the relation between commodity prices and yields we start from a simple present value model.[7] Define P_t to be the spot price of a commodity, and D_t to be a benefit from having the commodity available, i.e. the convenience yield net of storage and insurance costs[8]. Then, the net return on a commodity from period t to period $t+1$ is[9]:

$$R_{t+1} = \frac{P_{t+1} - P_t + D_t}{P_t}. \tag{1}$$

Assuming that the expected returns are constant, i.e. $E_t\left[R_{t+1}\right] = \mu$, and solving for P_t gives the present value model for a commodity spot price:

$$P_t = \sum_{i=1}^{\infty} \frac{E_t D_{t+i-1}}{(1+\mu)^i}. \tag{2}$$

[6] In order to ensure large number of observations the portfolios can be rebalanced so that they include new listings and exclude delisted assets.

[7] A similar approach is used by Pindyck (1993).

[8] Later in the empirical study next to comodity futures we also use financial futures. For index futures P_t is the index, and D_t are dividends (analagously to common stocks); for foreign currency futures P_t is the spot price of the currency, and D_t are the interests payments from a foreign deposit.

[9] Notice that the definition of a commodity return that is used here differs from commonly used commodity returns, $R_{p,t+1} = P_{t+1}/P_t - 1$, which consist of price changes only. Similar to total stock returns our definition includes the cash yield D_t.

A special case occurs when D_t is expected to grow at a constant rate g, in which case we obtain a standard Gordon-growth model:

$$P_t = \frac{D_t}{\mu - g},$$

implying that we can measure expected returns on commodities as the sum of the cash yields and growth rate in convenience yields:

$$\mu = \frac{D_t}{P_t} + g. \tag{3}$$

Dynamic versions of this approach are used by Bekaert and Harvey (2000) e.g. For many commodities, the growth rate g is - at least in the long run - close to zero, at least in real terms. If the growth rate for commodities is indeed close to zero, then it follows immediately from (3) that the yield measures the expected total return on commodities. We test this presumption below. Thus, next to the standard way of estimating expected returns using historical averages we have an alternative measure based on yields.

A natural way to estimate yields, is to use the information that is present in futures prices. Define $F_t^{(n)}$ to be the commodity futures price for delivery at time $t+n$. Assuming that the cost-of-carry model holds, we have:

$$F_t^{(n)} = P_t \exp\{-y_t^{(n)} \times n\}, \tag{4a}$$

$$f_t^{(n)} = p_t - n \times y_t^{(n)}, \tag{4b}$$

where $p_t = \log(P_t)$, $f_t = \log(F_t)$ and $y_t^{(n)}$ is the per-period yield for maturity n. By a no arbitrage argument, this yield is equal to the net cash yield (i.e. the cash flow D_t expressed as the percentage of price: $s_t = d_t - p_t$) minus the n-period interest rate:

$$y_t^{(n)} = s_t^{(n)} - i_t^{(n)}. \tag{5}$$

Then, a one-period log futures return can be decomposed in the following way:

$$z_{t+1}^{(1)} = p_{t+1} - f_t^{(1)} \tag{6a}$$

$$= p_{t+1} - p_t + y_t^{(1)} \tag{6b}$$

$$= r_{p,t+1} + s_t^{(1)} - i_t^{(1)} \tag{6c}$$

$$= r_{t+1} - i_t^{(1)} \tag{6d}$$

Thus, the one-period futures return is like an excess return on the total commodity return. Therefore, given the relation between yields and expected total returns from (3), we can relate futures returns to yields in the following way:

$$z_{i,t+1}^{(1)} + i_t^{(1)} = a_i + b_i s_{i,t}^{(1)} + e_{i,t+1}.$$

Subtracting the interest rate $i_t^{(1)}$ from both sides gives

$$z_{i,t+1}^{(1)} = \alpha_i + \beta_i y_{i,t}^{(1)} + \varepsilon_{i,t+1}. \tag{7}$$

Equation (7) shows that it is very natural to relate futures returns to yields.

[Please insert Table 1 here]

Table 1 confirms the presumption of a zero growth rate in futures yields. The table reports average growth rates, their standard errors and the t-statistics for testing the significance of means. We estimate growth rates for 25 futures contracts in our sample as the historical averages of the growth rates in cash yields. The results confirm that, indeed, all growths are almost zero, i.e., at any reasonable level of significance the historical averages of growth in cash yields are statistically indistinguishable form zero.

[Please insert Figure 1 here]

Given that the estimated growth rates are insignificant, we expect a strong relation between the two measures for expected returns: return- and yield-based measure. Figure 1 depicts the cross-sectional relation between the annualized average log returns on the nearest-to maturity futures contracts, and the corresponding annual log yield. The plotted lines represent fitted values from the following cross-sectional regression of mean futures returns on mean yields:

$$\overline{z}_i = \alpha + \beta \overline{y}_i + u_i.$$

The solid line depicts results from a regression with an intercept and the starred line from the regression without an intercept. This figure shows a strong, positive relation between mean returns and yields. This is confirmed by the high estimated R^2 of the the above regression: 61.3% of the cross-sectional variation in mean returns is explained by the cross-sectional variation in mean yields. The results are reported in Panel A of Table 2. The estimated intercept $\widehat{\alpha}$ is 2.6% per annum (with standard error of 0.007).[10] The estimated $\widehat{\beta}$ is in both cases (when we force an intercept to be zero and not) within two standard errors from one. When we do not impose restrictions on the intercept $\widehat{\beta}$ is equal to 1.09 (standard error of 0.18), and when we force an intercept to be zero, it slightly decreases to 0.88 with a standard error of 0.21.

[Please insert Table 2 here]

[10] When β in the cross-sectional regression is restricted to be one, then the intercept is equal to 2.5% pa with a standard error of 0.007 and it can be interpreted as the average growth rate in yields over all 25 futures contracts.

So far we looked at relation between returns and yields in the pooled cross-sectional regressions. Alternatively, we can use (7) directly in time-series regressions per commodity. Panel B of Table 2 presents these results. When monthly returns are used, the average (absolute) $\widehat{\beta}$ is almost zero (i.e. 0.10 with standard error of 0.06). However, when we move to lower frequency data the estimate increases in magnitude to 0.95 (standard error of 0.49) for yearly returns. The intercept increases as well, but across all frequencies it is not statistically different from zero. The most striking result in Table 2 is the low R^2 in the time-series regressions in comparison to the cross-sectional regression. Although the magnitude of R^2 increases as we move from higher frequency data to the lower frequency, nevertheless it remains far from 61.3% for the cross-sectional regression. The evidence that the cross-sectional relation is strong, but the time-series relations are weak, is also found in the literature on the forward premium puzzle in currency markets (see, e.g., Bansal and Dahlquist (2000)). Baillie and Bollerslev (2000) show that the univariate results should be interpreted with caution, since the weak time-series evidence may simply be a statistical artifact from having small samples and persistent autocorrelation, which results in a slower convergence to the true parameters value. Since pooling the data mitigates this problem, our main focus is on the cross-sectional results.

2.2 Consumption-based models for expected returns

According to finance theory, expected returns on assets are determined by their exposure to systematic economy wide risk. Rubinstein (1976) and Breeden (1979) show that the risk of an asset is determined by its covariance with consumption growth (CCAPM). In this framework, a representative agent allocates her resources among consumption and different investments opportunities in order to maximize her utility over lifetime consumption:

$$E\left[\left(\sum_{s=t}^{\infty}\delta^{s}u\left(C_{s}\right)\right)\mid F_{t}\right], \tag{8}$$

where we assume a time and state separable Von Neumann-Morgenstern utility function $u(\cdot)$, C_s denotes consumption expenditures in period s, δ is the time discount factor, and F_t denotes the information set available to the representative agent at time t. The first order conditions of the agent's maximization problem subject to the standard budget constraints imply the following relation that is satisfied by all financial assets:

$$E_t\left[\left(\delta^{j}\frac{u'\left(C_{t+j}\right)}{u'\left(C_t\right)}\right)r_{i,t+j}\right]=0 \tag{9}$$

where $r_{i,t+j}$ is the excess return on any asset i, from date t to $t+j$, $u'(\cdot)$ denotes first derivative of the period utility function, and $E_t[\cdot]$ denotes the expectation conditioned on the information available at time t.

2.3 The unconditional consumption CAPM

In the empirical analysis we will work with both the unconditional and conditional versions of (9). We start with the unconditional model. Defining the stochastic discount factor (SDF) as

$$m_{t+j} \equiv \delta^j \frac{u'(C_{t+j})}{u'(C_t)}$$

gives:

$$\begin{aligned} E\left[m_{t+j} r_{i,t+j}\right] &= 0 \\ &\iff E\left[r_{i,t+j}\right] = -\frac{Cov\left[r_{i,t+j}, m_{t+j}\right]}{E\left[m_{t+j}\right]} \end{aligned}$$

where the second equality follows from using the definition of covariance and by applying the law of iterated expectations. Defining the sensitivity of excess returns $r_{i,t+j}$ to changes in the stochastic discount factor as $\beta_{ic,j} = \frac{Cov[r_{i,t+j}, m_{t+j}]}{Var[m_{t+j}]}$ and the market price for SDF risk $\lambda_c = -\frac{Var[m_{t+j}]}{E[m_{t+j}]}$ we get

$$E\left[r_{i,t+j}\right] = \lambda_c \beta_{ic,j}. \tag{10}$$

This is the standard beta representation of the unconditional consumption CAPM. Expected excess returns on different assets are determined by their covariances with the stochastic discount factor, and thus by their covariances with consumption. An asset with greater consumption risk has a higher expected return, since consumption and marginal utility are inversely related.

2.4 The conditional consumption CAPM

To model the implications of the conditional version of (9):

$$E_t\left[r_{i,t+j}\right] = \lambda_{0c,t} + \lambda_{1c,t}\beta_{ic,t}, \tag{11}$$

on the unconditional expected returns, we follow Jagannathan and Wang (1996). First, take unconditional expectations of (11):

$$E\left[r_{i,t+j}\right] = \lambda_{0c} + \lambda_{1c}\overline{\beta}_{ic} + Cov\left[\lambda_{1c,t}, \beta_{ic,t}\right] \tag{12}$$

where $\overline{\beta}_{ic} = E\left[\beta_{ic,t}\right]$ is the expectation of $\beta_{ic,t}$. Then, projecting $\beta_{ic,t}$ on the conditional market risk premium $\lambda_{1c,t}$, gives:

$$\beta_{ic,t} = \overline{\beta}_{ic} + \varphi_{ic}\left(\lambda_{1c,t} - \lambda_{1c}\right) + \eta_{ic,t} \tag{13}$$

with $E\left[\eta_{ic,t}\right] = E\left[\eta_{ic,t}\lambda_{1c,t}\right] = 0$. Finally, substituting (13) into (12) gives for the unconditional expected returns:

$$\begin{aligned} E\left[r_{i,t+j}\right] &= \lambda_{0c} + \lambda_{1c}\overline{\beta}_{ic} + Var\left[\lambda_{1c,t}\right]\varphi_{ic}, \\ \varphi_{ic} &= \frac{Cov\left[\lambda_{1c,t}, \beta_{ic,t}\right]}{Var\left[\lambda_{1c,t}\right]}. \end{aligned}$$

Thus, the conditional CCAPM leads to a two-factor unconditional model, where the second factor is a risk premium induced by the covariance between the conditional $\beta_{ic,t}$ and the conditional market risk premium for consumption risk $\lambda_{1c,t}$. Not only assets with higher expected betas have higher unconditional expected returns, but also assets with betas that vary more with the market risk premium have higher unconditional expected returns.

The conditional model expressed in this way requires estimation of the expected beta $\overline{\beta}_{ic}$ and the sensitivity of the conditional beta to the market risk premium φ_{ic}, which cannot be done directly and requires additional assumptions. Since $\eta_{ic,t}$, the residual in the projection equation (13), does not affect the unconditional expected returns, we can ignore it, which leads to the following unconditional betas:

$$\begin{aligned}\beta_{ic} &\equiv \frac{Cov\left[r_{i,t+j}, m_{t+j}\right]}{Var\left[m_{t+j}\right]},\\ \beta_{i\varphi} &\equiv \frac{Cov\left[r_{i,t+j}, \lambda_{1c,t}\right]}{Var\left[\lambda_{1c,t}\right]}.\end{aligned}$$

Under mild assumptions the unconditional expected return is a linear function of the above two unconditional betas:

$$E\left[r_{i,t+j}\right] = \lambda_{0c} + \lambda_{1c}\beta_{ic} + \lambda_{i\varphi}\beta_{i}\varphi. \tag{14}$$

2.5 Ultimate consumption risk

Recently, Parker and Julliard (2005) find that contemporaneous consumption risk, as in the models discussed in the previous sections, is not sufficient to explain the cross-section of stock returns. They propose to extend the contemporaneous measure with the subsequent time periods to account for possible slow consumption adjustment. To see this, let us rearrange the terms in (9) in the following way:

$$E_t\left[u'\left(C_{t+j}\right)r_{i,t+j}\right] = 0.$$

Combining the above with the Euler equation for the risk-free rate between time $t+j$ and $t+j+S$:

$$E_{t+j}\left[\delta u'\left(C_{t+j+S}\right)R^f_{t+j,t+j+S}\right] = u'\left(C_{t+j}\right),$$

gives the following representation for expected returns:

$$\begin{aligned}E\left[r_{i,t+j}\right] &= \lambda_{c,S}\beta_{ic,S}, \qquad (15)\\ \beta_{ic,S} &= \frac{Cov\left[r_{i,t+j}, m^S_{t+j}\right]}{Var\left[m^S_{t+j}\right]},\\ m^S_{t+j} &= \delta R^f_{t+j,t+j+S}\frac{u'\left(C_{t+j+S}\right)}{u'\left(C_t\right)},\end{aligned}$$

where $Cov\left[m^S_{t+j}, r_{i,t+j}\right]$ for large S is referred to as *ultimate* consumption risk and the market price of this risk is $\lambda_{c,S} = -\frac{Var\left[m^S_{t+j}\right]}{E\left[m^S_{t+j}\right]}$.

We apply this approach to measure consumption risk in futures contracts. However, there are important differences between the consumption betas in stock and in futures markets. First, for futures it is common to observe positive as well as negative consumption betas, a feature less common in equity markets. Second, as Breeden (1980) shows, the contemporaneous consumption beta for longer maturity futures is usually lower than shorter maturity futures, due to supply responses. He argues that for short time-to-maturity futures, supply elasticities may be assumed to be near zero and demand elasticities to be relatively small. As the time-to-maturity increases supply responses start to affect consumption-betas. This suggests that the time over which the consumption risk is measured will play an important role in determining the consumption risk in futures markets.

3 Estimation issues

We use the two stage cross-sectional regressions (CSR) approach of Fama and MacBeth (1973) with an additional correction to the standard errors (i.e., correcting for the fact that $\beta's$ are pre-estimated as suggested by Shanken (1992) and Jagannathan and Wang (1996)). Moreover, since our sample consists of return histories that differ in length, we apply the procedure of Stambaugh (1997) to compute the multivariate moments without discarding any observations.

To parametrize the consumption-based models we assume that the period utility function has a constant relative risk aversion γ. This implies the following for the stochastic discount factor:

$$m_{t+j} = \delta^j \left(\frac{c_{t+j}}{c_t} \right)^{-\gamma},$$

where $\left(\frac{C_{t+j}}{C_t} \right)^{-\gamma}$ is the period j growth in per capita consumption from time t to time $t+j$. Given the above representation of the SDF, expected returns are a non-linear function of consumption growth. In the following, we assume that consumption growth and asset returns are jointly log-normally distributed, which implies that the expected excess returns are linear in the log-consumption growth:

$$E\left[r_{i,t+j}\right] + 0.5Var\left[r_{i,t+j}\right] = \gamma Cov\left[r_{i,t+j}, \Delta c_{t+j}\right], \tag{16}$$

where $\Delta c_{t+j} \equiv \log \left(\frac{C_{t+j}}{C_t} \right)$. The above can be also expressed in the following beta representation:

$$E\left[r_{i,t+j}\right] = \lambda_0 + \lambda_c \beta_{ic,j}, \tag{17a}$$

$$\beta_{ic,j} = \frac{Cov\left[r_{i,t+j}, \Delta c_{t+j}\right]}{Var\left[\Delta c_{t+j}\right]}. \tag{17b}$$

where the implied coefficient of relative risk aversion is $\gamma = \frac{\lambda_c}{Var[\Delta c_{t+j}]}$ and the intercept is $\lambda_0 = -0.5Var\left[r_{i,t+j}\right]$. A similar beta representation can be obtained using a Taylor series approximation of the stochastic discount factor around expected consumption growth.

In order to account for possibly slow consumption adjustment the log-consumption growth is measured over an extended horizon[11]:

$$\Delta c_{t+j}^{S} = \log\left(\frac{C_{t+j+S}}{C_t}\right). \tag{18}$$

In addition, the conditional model requires observations on the conditional market risk premium $\lambda_{1c,t}$. We follow the approach of Jagannathan and Wang (1996) utilizing the fact that a variable that helps predict the business cycle can also forecast the market risk premium. The logic behind this is based on the presumption that if prices vary over the business cycle, so might the market risk premiums. The literature on predictability has identified several potential variables, from which the most widely used are: a dummy for the January effect; a credit risk premium defined as the difference in yields between Moody's Baa rank bonds and Moody's Aaa rank bonds; a term structure premium defined as the difference between 90 days and 30 days Treasury Bill rate; a dividend yield on the S&P 500 index; and the return on the market index (see, e.g., Kirby (1998), Pesaran and Timmermann (1995), and Ferson and Harvey (1991)). Based on previous literature we use a term structure variable $\left(r_{t+1}^{term}\right)$[12] and estimate the following conditional model:

$$E\left[r_{i,t+j}\right] = \lambda_{0c} + \lambda_{1c}\beta_{ic} + \lambda_{i\varphi}\beta_{i,term} \tag{19a}$$

$$\beta_{ic} \equiv \frac{Cov\left[r_{i,t+j}, \Delta c_{t+j}\right]}{Var\left[\Delta c_{t+j}\right]}, \tag{19b}$$

$$\beta_{i,term} \equiv \frac{Cov\left[r_{i,t+j}, r_{t+j}^{term}\right]}{Var\left[r_{t+j}^{term}\right]}. \tag{19c}$$

4 Data

4.1 Futures data

We use data on 25 futures contracts that are obtained from the Futures Industry Institute (FII) Data Center. The starting date of our sample period varies between contracts, as we use all available information for each futures contract. The earliest starting date is February 1968. The end date, December 2004, is common for all series. Hence the number of observation varies between futures contracts in our sample.

The data can be divided into 20 commodity futures contracts and five financial futures contracts[13]. The commodities include grains (3), oil and meals (3), meats (4), energy (3), precious metals (4), and food and fiber (3). The financial contracts include an equity index (1) and foreign currencies (4). These markets have relatively large trading volumes and provide a broad cross-section of futures contracts.

[11] See Appendix A for details.

[12] We also experimented with other predictive instruments, but our results are robust with respect to the choice of the instrument.

[13] The classification we use is similar to the one used by the Institute for Financial Markets (IFM).

Details about the delivery months, the exchanges where these futures contracts are traded and the starting dates for each contract are in Table 3.

As outlined in Section 2, our dependent variable - the expected return - is measured in two ways: based on returns and yields. Futures returns are calculated using a rollover strategy of nearest-to-maturity futures contracts. Until the delivery month, we assume a position in the nearest-to-maturity contract. At the start of the delivery month, the position is changed to the contract with the following delivery month, which then becomes the nearest-to-maturity contract. Prices of futures observed in the delivery month are excluded from the analysis to avoid irregular price behaviour that is common during the delivery month. Depending on the delivery dates during the year, the different series are for delivery one to three months apart. We obtain a minimum of 194 and a maximum of 442 observations.

The second measure of expected returns, derived from the present value model, is based on the futures yields. To avoid the problems of seasonal fluctuations in futures (convenience) yields, yearly yields are used. We construct the series of annual yields as the log price difference between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts. Depending on the series, the maturities vary between 7 to 13 months. To correct for the varying length of the spread, we use yields projected on the maturity equal exactly 12 months.

[Please insert Table 4 here]

Descriptive statistics are presented in Table 4. Panel A describes the returns on 25 futures markets. The first, three columns give the annualized mean returns computed for different frequencies. Consistent with previous studies (e.g. Bessembinder (1992), Bessembinder and Chan (1992), and DeRoon, Nijman, and Veld (2000)) we find that except for a few futures contracts (S&P 500, crude oil, unleaded gasoline and live cattle futures) the estimated mean returns are statistically indistinguishable from zero at the 5% significance level. The highest average returns - more than 10% on an annual basis - are earned by energy futures. For some futures, e.g. soybean oil, cotton, coffee, and copper, we observe large differences in mean returns across the different frequencies of the data. Finally, the last column gives the annualized yields for different futures. The table shows that the cross-section of mean yields is smoother than mean returns. For instance, the dispersion between the minimum and the maximum yield is smaller than for the mean returns.[14]

[14] We sometimes observe rather extreme returns, usually related to specific events. One example is the silver bubble in the turn of 1979. By the early 1970s silver began to rise in price, along with gold, platinum, oil, inflations and U.S. interest rates. The Commodities Futures Trading Commision falsly attributed the rise in silver prices to the market manipulations and changed the trading rules (i.e., margin requirements were rised to 100%, only futures sell orders were allowed), which lead to a collapse of the silver bubble. This is reflected in our data, where we observe almost 300% annual return for silver

4.2 Consumption data

It is a well known fact that reported consumption data are subject to measurement problems. Theory implies that consumption risk is measured with respect to aggregate consumption growth between two points in time. In practice, however, we observe total expenditures on goods and services over a period of time. This creates a so called "summation (or time-aggregation) bias" (see, e.g., Breeden, Gibbons, and Litzenberger (1989)).

One way to avoid this problem is to use higher frequency consumption data. On the other hand, high frequency consumption data are measured less precisely, which may lead to less reliable (less stable) estimates. The higher frequency data may exhibit seasonal patterns, which might be especially important among the returns on commodity futures.[15] Moreover, recent work by Jagannathan and Wang (2005) shows that consumption-risk measured with lower frequency data, can better explain the cross-section of the 25 Fama-French portfolios. Since establishing which of the aforementioned biases dominate in the futures markets remains an empirical issue, we use monthly, quarterly and yearly consumption data in our empirical tests.

Following the literature, we measure consumption growth as the percentage change in the seasonally adjusted, aggregate, real per capita consumption expenditures on nondurable goods and services. We use monthly, quarterly and annual consumption and population data from the National Income and Product Accounts (NIPA) tables in Section 2 on Personal Income and Outlays. The sample period is dictated by the availability of the futures prices, as the consumption data at all frequencies are observed at a longer time interval.

Panel B of Table 4 gives the descriptive statistics for the log consumption growth. The consumption growth during our sample period is slightly above 2% per annum for all frequencies. Monthly consumption exhibits the highest growth and the highest volatility.

4.2.1 *Benchmark factors*

For the benchmark models we use the standard benchmark research factors as given in Kenneth French's online data library. As these data are only available on a monthly and an annual basis, we compute quarterly returns by compounding monthly returns. Panel C of Table 4 gives the descriptive statistics for the benchmark factors, which confirms their standard features. In contrast to the mean futures returns given in Panel A, benchmark factors mean returns do not vary substantially across different frequencies.

in 1979. In general we observe more volatility in the futures data, which is reflected in rather high standard deviations reported earlier. Since, these are inherent features of futures data we do not exclude any observations.

[15] For example, futures contracts on grains may exhibit seasonality around (due to) the harvest times.

5 Empirical analysis

5.1 Unconditional models

The starting point of our empirical analysis is the unconditional version of the CCAPM in Equation (17). Table 5 provides the cross-sectional estimates of λ_0 and λ_c, based on our 25 futures contracts. Panel A reports the regression estimates for betas estimated at different frequencies: monthly, quarterly and yearly. Estimating beta at a monthly frequency leads to a very poor performance of the consumption model. The R^2 of the cross-sectional regression is zero, and the market price of consumption risk is even slightly negative, although not significantly different from zero.

[Please insert Table 5 here]

At lower frequencies, the CCAPM fares much better: for quarterly estimates, the R^2 increases to 52% and for yearly estimates it is 23%. A similar pattern shows up for the simple CAPM and the Fama-French three factor model: all models have the highest R^2 for quarterly estimates, and essentially zero R^2s for monthly estimates. However, for both quarterly and yearly estimates, the consumption model exhibits by far the best performance, whereas the R^2 for the CAPM never exceeds six percent. The implied consumption risk premium, λ_c, is about one percent based on quarterly estimates and 65 basis points based on yearly estimates. These estimates are somewhat lower than the estimates found by Jagannathan and Wang (2005) based on stock portfolios, but the order of magnitude and the patterns that we find are comparable, except for the fact that for our futures data quarterly estimates provide the best results.

Panel B of Table 5 reports similar results, but here we use the average futures yields as a measure of expected return. The results in Panel B demonstrate again the best performance for quarterly estimates, but now the Fama-French three factor model exhibits the highest R^2 (46%), whereas the CAPM and the CCAPM show similar performances in terms of R^2 (26% and 29% respectively). However, both the CAPM and the Fama-French model imply negative market risk premiums, λ_{mkt}, whereas the CCAPM consistently yields positive consumption risk premiums for the quarterly and yearly estimates. The risk premium λ_c is now only about half the premium that we found in Panel A.

[Please insert Figure 2 here]

Figure 2 illustrates these findings graphically. This figure illustrates, that even though it is more difficult to explain the cross section of yields (as follows from the R^2s), the pricing errors that result from using the yields as an expected return measure are much smaller than the pricing errors that follow from using the mean returns. This basically follows from the lower volatility in yields versus mean returns and is confirmed in the estimates of the absolute pricing errors. We measure pricing errors as the absolute value of the error term implied by the cross-section regression. When mean past returns are used the smallest pricing errors are implied by the consumption-based model (i.e., 3.0%, while both the CAPM and the FF models imply 4.1%). Moreover, for all models these pricing errors are above the ones implied by the yield-based expected returns. These latter errors are similar across all models (i.e., 2.6%, 2.9%, and 2.4% respectively), though Fama-French three factor model yields the lowest errors.

Thus, based on the R^2s and the sign of the risk premiums, the CCAPM explains the cross section of expected futures returns best using quarterly estimates, whereas the CAPM shows the worst performance for the unconditional models.

5.2 Conditional models

Table 6 provides the estimates based on the conditional CCAPM in (19). Similar to Table 5, we report estimates based on average futures returns in Panel A and estimates based on yields as an expected return measure in Panel B.

[Please insert Table 6 here]

Panel A shows that for all frequencies the conditional models show a much better performance than the unconditional models in Table 5. It is only for the quarterly estimates of the consumption model that the R^2 is less than ten percent higher for the conditional model (59% versus 52%). In all other cases the R^2 improves by at least ten percent, and often more than 20%.

Unlike the unconditional models, the performance of the models now improves monotonically as the estimation frequency lowers. Using monthly estimates, the Fama-French model shows the highest R^2, although the differences between the three models are small. Also, both the CAPM and the Fama-French model yield negative market risk premiums, whereas the CCAPM implies a positive premium at all frequencies. For quarterly and yearly estimates, the CCAPM shows the best performance by far, with consistently positive consumption premiums λ_c. The explanatory power of the CCAPM is the highest for the yearly estimates (60%), but the difference with the quarterly estimates is small. The estimated consumption risk premium and the implied risk aversions are close to the ones in Table 5.

When we use yields as the expected return measure, a similar pattern arises as for the unconditional results in Table 5. All models show the best performance again using quarterly estimates, and the Fama-French model achievs the highest R^2 at every frequency. However, as with the unconditional model, the conditional CAPM and Fama-French model always yield negative market risk premiums λ_{mkt}, whereas the consumption model premiums are positive for both the quarterly and the yearly estimates. Again, models estimated on yield-based expected returns imply lower pricing errors (i.e., CCAPM 2.6%, CAPM 2.4%, and FF model 2.2%) than those estimated with returns-based expected returns (i.e., 2.8%, 3.7%, and 3.5% respectively). For the return-based measure of expected returns CCAPM outperforms the other model when looking at pricing errors.

5.3 Ultimate Consumption Risk

Table 7 reports the performance of the (unconditional) CCAPM based on ultimate consumption risk for different horizons S in (18). Panel A shows the results using the mean futures returns again, and Panel B the results using the mean yields as the dependent variable in the cross sectional regression. First, the reults based on monthly mean returns indicate that the R^2 first increases until the horizon is about six months, and then starts to decrease. However, the monthly mean returns almost invariably yield negative market prices of consumption risk. For the quarterly and annul returns the price of consumption risk is always positive, but here our results are contradictory to those of Parker and Julliard (2005). Where Parker and Juliard find an increasing performance as the number of quarters increases, we find the best performance for the contemporaneous first quarter, after which the performance of the ultimate risk measure deteriorates. Using yields as the expected return measure confirms this finding and even yields negative prices of consumption risk for longer horizons S.

[Please insert Table 7 here]

The results for the conditional CCAPM (Table 8) basically confirm these findings. As in the previous tables, the performance of the conditional model improves significantly on the unconditional one. However, the main finding for the ultimate risk is similar to the one in Table 6: After the first contemporaneous quarter (year), the performance of the model actually decreases by increasing the ultimate risk horizon, rather than increasing as in Parker and Julliard (2005).

[Please insert Table 8 here]

This difference in the performance of the ultimate risk for our futures data relative to stock market data needs further analysis. As outlined in Breeden (1980) and French (1986) for instance, for commodity betas demand and supply elasticities may play an important role. For instance, a positive demand shock will for many commodities lead to higher prices, but will also be associated with higher consumption, implying a positive short term beta. Following the demand shock however, demand may lower (because of a negative price elasticity) and supply may gradually increase, which both have offsetting effects on the relation between commodity prices on the one hand and longer term consumption on the other hand. Similarly, following a positive supply shock, prices will decrease and consumption will increase, leading to a negative short-term beta. Again, changes in demand and supply for the commodity following the price change will have off-setting effects in the longer run.

[Please insert Table 9 here]

Table 9 provides some support for this, based on the consumption betas of our futures contracts. For each futures contract, the beta is reported w.r.t. the contemporaneous quarter consumption growth, as well as w.r.t. longer horizon consumption growth. As the table shows, for almost every futures contract the betas decrease in absolute value as the horizon increases, basically fading out to zero. This is consistent with the hypothesis formulated above that for commodities - which are part of aggregate consumption - supply and demand changes induce short term consumption betas, but basically zero longer term consumption betas. This may also explain the fact that in Table 5 and 6 we find the strongest relation between consumption growth and futures returns at the quarterly horizon and not at the annual horizon: decreasing the frequency from monthly to quarterly returns and consumption growth reduces the estimation error in consumption data, but a further decrease in the frequency actually decreases the performance because of the changing consumption betas.

[Please insert Table 10 here]

Table 10 gives some further support for the supply and demand effects on futures returns. Here we estimate the two-factor production based asset pricing model as outlined in Cochrane (1991, 1996). Production factors are modelled by growth in both residential and non-residential investments (derived from the NIPA tables). Similar to ultimate risk, we conjecture that production or investment may react only slowly to commodity price changes, implying that an ultimate investment growth measure (analogous to the ultimate consumption growht measure described above), may better explain futures returns than contemporaneous investment growth. Table 10 supports this. For instance, based on quarterly returns, we see that the cross-sectional R^2 of the production based asset pricing model first increases until two quarters following the futures return, and then starts to decrease again. This pattern shows up both when using mean futures returns and yields as expected return measures.

Thus, to the extend that commodity price changes are followed by changes in demand and supply, this may explain why ultimate consumption risk is not a good risk measure for commodities, unlike for stocks.

6 Summary and Conclusions

Recent studies on consumption based models show that measuring consumption growth and/or returns over longer horizon improves the performance of the CCAPM in explaining the cross-sectional variation of expected stock returns. Drawing on these results, we study whether excess returns on futures contracts vary in a systematic way due to differences in consumption risk similarly to the returns on stocks. Historically, commodity futures have earned excess returns similar to those of equities (Gorton and Rouwenhorst (2004)). Nevertheless, they fulfill different economic function than corporate securities such as stocks, i.e. they do not represent claims against future cash flows of the firm, but bets on the future expected spot prices of commodities. They also constitute a broader class of assets than simply stock returns, since they are related to the underlying values of various commodities (agriculturals, meats, energy and precious metals), as well as currencies and an equity index.

In this paper, we show that, similarly to stock returns, the (unconditional) CCAPM explains about 50 percent of the cross section of futures returns at the quarterly frequency, while there is almost no explained variance at the monthly level, and an intermediate result at the yearly level. The conditional model yields even better performance than the unconditional model (i.e., the R^2 is about 60 percent) and, again, it is best at the quarterly and annual frequency. In both cases, the CCAPM explains the futures returns much better than either the CAPM or Fama-French model.

Using the average yield as the measure of expected returns in the cross-sectional regression confirms that the CCAPM performs best at the quarterly frequency. However, the model can explain only up to 29 percent of the cross sectional variation in yields in the unconditional case and up to 36 percent in the conditional case. The Fama-French model can explain the cross sectional variation in yields much better (up to 45 and 55 percent resp.), but yields negative estimates of the market risk premia.

Finally, using ultimate consumption risk, we find that the performance of the CCAPM is best using consumption growth of the contemporaneous quarter of the returns, but then deteriorates for the longer horizons. Although this contradicts the findings of Parker and Julliard (2005) for stock returns, it is consistent with the finding that the CCAPM performs best at the quarterly frequency and may be the result of supply and demand elasticities of many of the commodities that underlie our futures contracts, inducing time-varying consumption betas. Future research should address the effect of supply and demand changes on expected futures returns more carefully.

Appendix A Log-linearization for ultimate risk horizon

The assumption on joint log-normality of consumption growth and returns implies the following for expected returns:

$$E\left[r_{i,t+j}\right] = -\log\delta + \gamma E\left[\log\left(\frac{C_{t+j}}{C_t}\right)\right] + 0.5\left(\sigma_i^2 + \gamma^2\sigma_c^2 - 2\gamma\sigma_{ic}\right).$$

Next, consider the excess returns on the assets of the following form:

$$E\left[r_{i,t+j}-r_t^f\right]=-0.5Var\left[r_{i,t+j}\right]+\gamma Cov\left[r_{i,t+j},\log\left(\frac{C_{t+j}}{C_t}\right)\right]. \tag{20}$$

Assuming that the the risk free rate of borrowing between time $t+1$ and $t+1+S$ is constant so that the consumption-CAPM holds in the following way:

$$E\left[r^f_{t+j,t+j+S}\right]=-\log\delta+\gamma_S E\left[\log\left(\frac{C_{t+j+S}}{C_{t+j}}\right)\right]+0.5\gamma_S^2\sigma_{c,S}^2,$$

which allows us to substitute out C_{t+1} in (20) and obtain:

$$E\left[r_{i,t+j}-r_t^f\right]+0.5Var\left[r_{i,t+j}\right]=\gamma Cov\left[r_{i,t+j},\log\left(\frac{C_{t+j+S}}{C_t}\right)\right]-\theta,$$

where $\theta=\frac{\gamma}{\gamma_S}Cov\left[r_{i,t+j},r^f_{t+j,t+j+S}+\log\delta-0.5\gamma_S^3\sigma_{c,S}^2\right]$ which is assumed to be zero. It follows immediately, that we can use the beta representation of the form:

$$\begin{aligned} E\left[r_{i,t+j}\right] &= \lambda_0+\lambda_c\beta_{ic,j}, \\ \beta_{ic,j} &= \frac{Cov\left[r_{i,t+j},\Delta c^S_{t+j}\right]}{Var\left[\Delta c^S_{t+j}\right]}. \end{aligned}$$

where $\Delta c^S_{t+j}=\log\left(\frac{C_{t+j+S}}{C_t}\right)$.

References

Baillie, Richard T., and Tim Bollerslev, 2000, The forward premium anomaly is not as bad as you think, *Journal of International Money and Finance* 19, 471–488.

Bansal, Ravi, and Magnus Dahlquist, 2000, The forward premium puzzle: Different tales from developed and emerging economies, *Journal of International Economics* 51, 115–144.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

Bekaert, Geert, and Campbell R. Harvey, 2000, Foreign speculators and emerging equity markets, *Journal of Finance* 55, 565–613.

Bessembinder, Hendrik, 1992, Systematic risk, hedging pressure, and risk premiums in futures markets, *Review of Financial Studies* 5, 637–667.

———, and Kalok Chan, 1992, Time-varying risk premia and forecastable returns in futures markets, *Journal of Financial Economics* 32, 169–193.

Black, Fischer, 1976, The pricing of commodity contracts, *Journal of Financial Economics* 3, 167–179.

Breeden, Douglas T., 1979, An intertemporal asset pricing model with stochastic consumption and investment opportunities, *Journal of Financial Economics* 7, 265–296.

——— , 1980, Consumption risk in futures markets, *Journal of Finance* 35, 503–520.

——— , Michael R. Gibbons, and Robert H. Litzenberger, 1989, Empirical test of the consumption-oriented CAPM, *Journal of Finance* 44, 231–262.

Campbell, John Y., and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.

——— , 2000, Explaining the poor performance of consumption-based Asset Pricing Models, *Journal of Finance* 55, 2863–2878.

Campbell, John Y., and Robert J. Shiller, 1988, Stock prices, earnings and expected dividends, *Journal of Finance* 43, 661–676.

Carter, Colin A., Gordon C. Rausser, and Andrew Schmitz, 1983, Efficient asset portfolios and the theory of normal backwardation, *The Journal of Political Economy* 91, 319–331.

Cochrane, John H., 1991, Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* 46, 209–237.

——— , 1996, A cross-sectional test of an investment-based asset pricing model, *The Journal of Political Economy* 104 (3), 572–621.

DeRoon, Frans A., Theo E. Nijman, and Chris H. Veld, 2000, Hedging pressure effects in futures markets, *Journal of Finance* 55, 1437–1456.

Dusak, Katherine, 1973, Futures trading and investor returns: An investigation of commodity market risk premiums, *The Journal of Political Economy* 81, 1387–1406.

Epstein, Larry G., and Stanley E. Zin, 1989, Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* 57, 937–969.

——— , 1991, Substitution, risk aversion and the temporal behavior of consumption and asset returns: An empirical analysis, *Journal of Political Economy* 99, 263–286.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Ferson, Wayne E., and Campbell R. Harvey, 1991, The variation of economic risk premiums, *Journal of Political Economy* 99 (2), 385–415.

French, Kenneth R., 1986, Detecting spot price forecasts in futures prices, *Journal of Business* 59, 39–54.

Gorton, Gary, and Geert K. Rouwenhorst, 2004, Facts and fantasies about commodity futures, *Working Paper*.

Jagannathan, Ravi, 1985, An investigation of commodity futures prices using the consumption-based intertemporal capital asset pricing model, *Journal of Finance* 40, 175–191.

———, and Yong Wang, 2005, Lazy investors, discretionary consumption, and the cross section of stock returns, *Working Paper, Northwestern University*.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 51, 3–53.

Kirby, Chris, 1998, The restrictions on predictability implied by rational asset pricing models, *The Review of Financial Studies* 11 (2), 343–382.

Merton, Robert C., 1980, On estimating the expected return on the market, *Journal of Financial Economics* 8, 323–361.

Parker, Jonathan A, and Christian Julliard, 2005, Consumption risk and the cross-section of expected returns, *Journal of Political Economy* 113, 185–222.

Pesaran, M. Hashem, and Allan Timmermann, 1995, Predictability of stock returns: Robustness and economic significance, *Journal of Finance* 50 (4), 1201–1228.

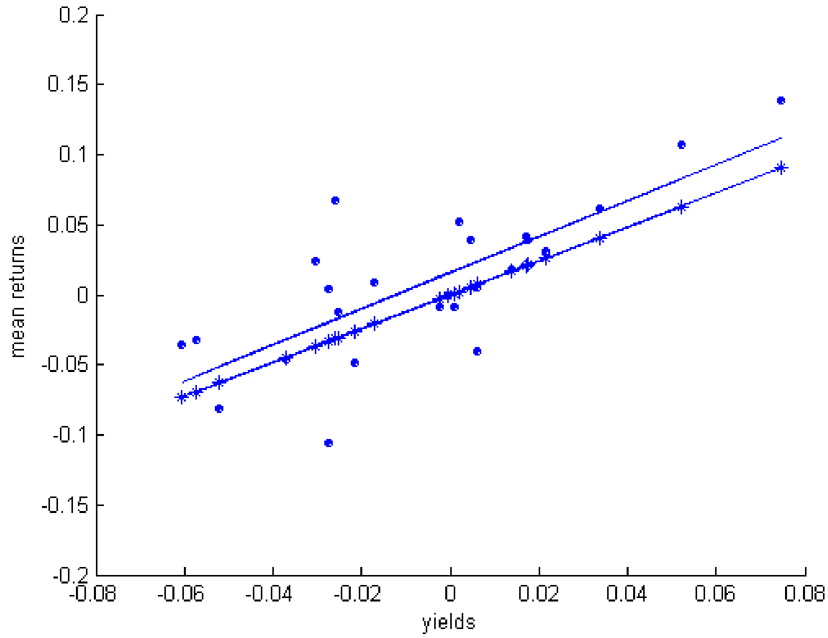
Pindyck, Robert S., 1993, The present value model of rational commodity pricing, *The Economic Journal* 103, 511–530.

Rubinstein, Mark, 1976, The valuation of uncertain income streams and the pricing of options, *The Bell Journal of Economics* 7, 407–425.

Shanken, Jay, 1992, On the estimation of beta-pricing models, *Review of Financial Studies* 5, 1–33.

Stambaugh, Robert F, 1997, Analyzing investments whose histories differ in length, *Journal of Financial Economics* 45, 285–331.

Figure 1: **The relation between mean returns and mean yields.**



The figure depicts the cross-sectional relation between the annualized average log returns on the nearest-to maturity futures contracts, and the corresponding annual log yield. The plotted lines represent fitted values from the following cross-sectional regression:

$$\overline{z}_i = \alpha + \beta \overline{y}_i + u_i.$$

The solid line depicts the results from the regression with an intercept and the starred line the results from the regression without an intercept.

Figure 2: **Fitted versus realized returns (quarterly).**

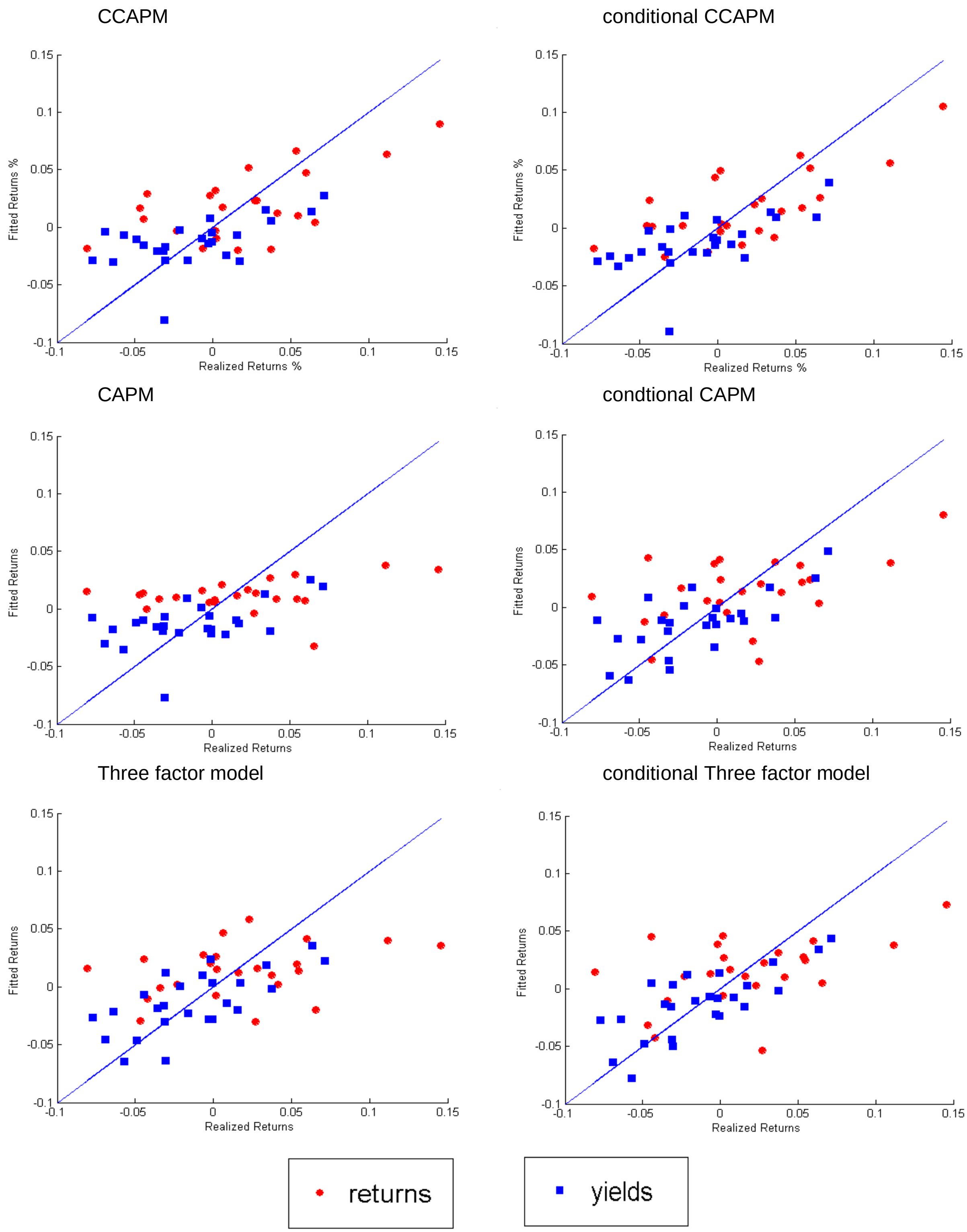


Table 1: **Historical growth rates in futures yields.**
The table gives the estimates of the annual average growth rates in cash yields for 25 futures contracts. The sample period varies across futures. The end of the sample period is always December 2004. The earliest starting date is February 1968 implying 442 observations, and the latest is October 1988 with 194 observations. The details on the exact starting dates for each futures contract are given in Table 3. The cash yield is defined in equations (4b) and (5) and is computed as the log price difference between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts, correcting for the varying length of spread, plus the interest rate over the same spread. Newey-West standard deviations are used.

Futures contract	Averages	Standard deviations	t-statistics
	Commodities		
Grains			
Wheat	3.16%	34.72%	0.61
Corn	2.86%	36.15%	0.51
Oats	-0.47%	47.63%	-0.07
Oil & Meal			
Soybean	4.66%	40.29%	0.79
Soybeans Oil	4.60%	42.92%	0.73
Soybean meal	1.97%	46.11%	0.28
Meats			
Live cattle	2.88%	30.84%	0.96
Feeder cattle	3.77%	22.53%	1.12
Live (lean) hog	3.27%	57.94%	0.44
Pork Bellies	2.55%	66.40%	0.33
Energy			
Crude Oil	1.73%	52.28%	0.19
Heating Oil	0.79%	48.54%	0.11
Unleaded Gasoline	1.95%	57.72%	0.22
Metals			
Gold	2.87%	20.06%	0.67
Silver	4.03%	32.99%	0.72
Platinum	5.05%	30.11%	1.02
Copper	0.62%	33.79%	0.08
Food/Fiber			
Coffee	-0.08%	48.13%	-0.01
Sugar	-6.86%	59.10%	-0.65
Cotton	1.37%	47.51%	0.19
	Financials		
Index			
S&P 500	9.54%	15.03%	2.86
Foreign Currency			
Japanese Yen	3.54%	13.55%	1.30
British Pound	-0.46%	11.95%	-0.21
Candian $	-1.00%	6.26%	-0.87
Swiss Frank	2.45%	13.78%	0.91

Table 2: **The relation between mean returns and yields.**
This table reports the estimates from the cross-sectional

$$\overline{z}_i = \alpha + \beta \overline{y}_i + u_i$$

and the time-series

$$z_{i,t+1} = \alpha_i + \beta_i y_{i,t} + \varepsilon_{i,t+1}$$

regressions of 25 futures log returns ($z_{i,t+1}$) on log yields ($y_{i,t}$). The sample period varies across futures. The end of the sample period is always Decmeber 2004. The earliest starting date is February 1968 implying 442 observations, and the latest is October 1988 with 194 observations. The details on the exact starting dates for each futures contract are given in Table 3. The yields are computed as the log price difference between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts, correcting for the varying length of spread. Panel A reports the results from the cross-sectional regression. In a regression without a constant the uncentred R^2 is reported. Panel B reports the results for the time-series regressions estimated on monthly, quarterly and yearly returns.

	Intercept	Slope	R^2
Panel A: Cross-section			
Coefficient	0.026	1.09	61.30
Standard deviation	0.007	0.18	
Coefficient		0.88	42.51
Standard deviation		0.21	
Panel B: Time-series			
Monthly			
Coefficient	0.006	0.10	1.14
Standard deviation	0.005	0.06	
Quarterly			
Coefficient	0.016	0.28	2.87
Standard deviation	0.013	0.16	
Yearly			
Coefficient	0.078	0.95	7.14
Standard deviation	0.046	0.49	

Table 3: **Futures contracts.**

The table reports the futures exchange, the delivery months, and the beginning date of the sample period for the 25 futures contracts in our sample. The end date of the sample period, December 2004, is common for all contracts.

Futures contract	Exchange	Delivery months	Start date
	Commodities		
Grains			
Wheat	Chicago Board of Trade	3,5,7,9,12	1968 Dec
Corn	Chicago Board of Trade	3,5,7,9,12	1968 Dec
Oats	Chicago Board of Trade	3,5,7,9,12	1974 Dec
Oil & Meal			
Soybean	Chicago Board of Trade	1,3,5,7,8,9,11	1968 Nov
Soybeans Oil	Chicago Board of Trade	1,3,5,7,8,9,10,12	1968 Nov
Soybean meal	Chicago Board of Trade	1,3,5,7,8,9,10,12	1968 Nov
Meats			
Live cattle	Chicago Mercantile Exchange	2,4,6,8,10,12	1976 Dec
Feeder cattle	Chicago Mercantile Exchange	1,3,4,5,8,9,10,11	1977 Oct
Live (lean) hog	Chicago Mercantile Exchange	2,4,6,7,8,10,12	1969 Dec
Pork Bellies	Chicago Mercantile Exchange	2,3,5,7,8	1969 Aug
Energy			
Crude Oil	New York Mercantile Exchange	All	1983 Dec
Heating Oil	New York Mercantile Exchange	All	1979 Dec
Unleaded Gasoline	New York Mercantile Exchange	All	1985 Apr
Metals			
Gold	Commodity Exchange, Inc.	1,2,4,6,8,10,12	1975 Jan
Silver	Commodity Exchange, Inc.	3,5,7,9,12	1968 Feb
Platinum	New York Mercantile Exchange	1,4,7,10	1972 Sep
Copper	Commodity Exchange, Inc.	1,3,5,7,9,12	1988 Oct
Food/Fiber			
Coffee	New York Board of Trade	3,5,7,9,12	1973 Dec
Sugar	New York Board of Trade	3,5,7,10	1974 Oct
Cotton	New York Board of Trade	3,5,7,10,12	1972 Dec
	Financials		
Index			
S&P 500	International Monetary Market	3,6,9,12	1982 Dec
Foreign Currency			
Japanese Yen	International Monetary Market	3,6,9,12	1976 Dec
British Pound	International Monetary Market	3,6,9,12	1975 Dec
Candian $	International Monetary Market	3,6,9,12	1977 Dec
Swiss Frank	International Monetary Market	3,6,9,12	1975 Dec

Table 4: **Descriptive statistics.**
The table gives the descriptive statistics for the 25 futures contracts, consumption growth and benchmark factors. The sample period varies across futures (see Table 3). The yields are computed as the log price difference between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts. To correct for the varying length of spread we use yields projected on the maturity equal exactly 12 months. Hence, the standard errors reported in the last column, correspond to the standard errors of these forecasted yields. Panel A describes the statistics for expected returns estimated from data for different frequency: monthly (M), quarterly (Q) and yearly (Y). Panels B and C give the same statistics for consumption growth and returns on the benchmark factors respectively.

	Annualized returns						Annualized Yields	
	Mean in %			Standard Deviation				
	M	Q	Y	M	Q	Y	Mean in %	St. Dev
Panel A: epxected returns								
Futures contract								
Wheat	-2.38	-1.96	0.16	23.8	26.3	34.9	-3.55	10.17
Corn	-4.58	-4.08	-3.28	23.6	25.3	28.5	-4.45	9.49
Oats	-8.17	-7.70	-7.09	29.4	31.8	32.6	-7.71	12.43
Soybean	0.57	0.61	0.81	27.1	28.6	28.0	-0.71	10.25
Soybeans Oil	3.97	3.52	6.77	31.1	31.3	45.0	-1.63	10.41
Soybean meal	2.06	2.43	2.85	29.8	31.4	32.4	-0.15	12.50
Live cattle	5.20	5.36	4.96	15.5	15.0	14.9	-0.28	6.17
Feeder cattle	3.96	4.14	3.33	14.9	15.3	19.7	-0.05	4.31
Live hog	3.12	2.76	1.66	26.9	27.0	26.3	1.53	16.05
Porl Bellies	-4.04	-5.22	-8.85	35.1	33.6	25.9	-4.90	13.23
Crude Oil	10.67	13.03	11.70	32.8	38.5	44.4	6.31	11.71
Heating Oil	4.15	6.24	4.42	30.3	34.3	35.2	3.37	11.02
Unleaded Gasoline	13.85	14.53	14.09	33.7	34.5	38.2	7.13	11.83
Gold	-3.16	-3.61	-2.71	19.4	19.4	28.8	-6.42	3.86
Silver	-3.59	-4.82	-1.04	31.7	32.1	58.4	-6.92	3.92
Platinum	2.44	1.37	1.92	28.9	25.3	32.0	-5.68	3.81
Copper	6.14	6.07	2.68	24.1	25.0	29.1	3.72	12.82
Coffee	0.85	1.49	3.52	38.3	44.5	53.1	-2.16	13.58
Sugar	-10.59	-9.22	-11.94	39.8	43.1	37.7	-3.13	15.12
Cotton	-0.01	0.23	4.26	24.6	26.8	38.6	-0.09	11.89
S&P 500	6.74	6.89	7.23	14.8	16.5	16.5	-3.03	1.89
Japanese Yen	0.46	0.26	0.52	12.8	14.1	16.2	-3.17	1.73
British Pound	1.87	1.59	1.90	10.9	11.1	15.4	1.70	1.39
Candian $	0.54	0.23	0.20	5.6	5.6	7.4	0.86	1.24
Swiss Frank	-0.29	-0.55	-0.59	13.0	14.4	15.9	-3.06	2.12
Panel B: consumption growth								
Consumption growth	2.08	2.07	2.04	1.2	0.8	1.1		
Panel C: benchmark factors								
MKT	5.35	5.68	5.48	16.0	18.0	18.3		
SMB	2.08	2.73	1.95	11.5	12.1	13.2		
HML	5.37	5.26	5.90	10.7	12.4	15.2		

Table 5: **Unconditional models.**
The table reports the cross sectional regression estimation results for the consumption-CAPM model and two benchmark models: CAPM and the three factor model:

$$E[r_{i,t+1}] = \lambda_0 + \lambda\beta_i.$$

We use 25 futures contracts with varying sample period (see Table 3). In Panel A expected returns are measured as the historical means of the returns, while in Panel B yields-based expected returns are used. γ is the implied coefficient of risk aversion defined as $\frac{\lambda_c}{Var[\Delta c_{t+1}]}$. The first row reports the coefficient estimates. Fama-MacBeth standard errors are reported in the second row, and Shanken corrected standard errors are in the third row.

	CCAPM				CAPM			Three factor model				
	λ_0	λ_c	R^2 (R^2_{adj})	γ	λ_0	λ_{mkt}	R^2 (R^2_{adj})	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	R^2 (R^2_{adj})
Panel A : mean returns												
monthly												
Coeff	1.20	-0.02	**0.00%**	-15	1.22	-0.39	**0.02%**	1.00	0.22	2.81	0.42	**0.67%**
St err	1.31	1.32	-4.35%		1.18	5.34	-4.32%	1.33	5.90	9.51	9.78	-13.52%
Corrected err	1.46	1.07			1.85	4.57		1.82	5.06	9.85	10.07	
quarterly												
Coeff	-0.64	1.01	**51.53%**	572	1.09	-4.70	**5.84%**	2.09	-5.69	-8.45	13.05	**19.75%**
St err	0.87	0.20	49.43%		1.11	3.93	1.75%	1.21	3.82	5.06	6.82	8.28%
Corrected err	2.20	0.47			1.80	4.47		2.17	5.47	6.05	8.75	
yearly												
Coeff	-1.54	0.65	**22.55%**	53	0.78	1.32	**0.60%**	0.46	1.66	2.47	-1.58	**5.03%**
St err	1.32	0.25	19.18%		1.09	3.54	-3.72%	1.18	3.64	2.73	3.78	-8.54%
Corrected err	2.18	0.34			1.84	3.09		2.01	4.19	3.91	5.52	
Panel B: yields												
monthly												
Coeff	-1.14	-0.30	**0.42%**	-241	-0.87	-5.61	**9.21%**	-0.66	-5.20	-2.66	-1.58	**10.92%**
St err	0.95	0.95	-3.91%		0.81	3.67	5.26%	0.91	4.03	6.50	6.68	-1.81%
Corrected err	1.62	1.39			2.13	5.15		2.17	5.28	12.94	13.46	
quarterly												
Coeff	-2.23	0.53	**28.71%**	297	-1.40	-6.85	**25.63%**	-0.52	-7.73	-10.00	6.81	**45.75%**
St err	0.74	0.17	25.61%		0.69	2.43	22.40%	0.70	2.19	2.90	3.90	38.00%
Corrected err	1.87	0.45			1.81	4.81		2.12	5.17	6.46	10.34	
yearly												
Coeff	-2.21	0.25	**6.43%**	21	-1.30	-0.46	**0.14%**	-1.82	-0.10	0.24	-4.88	**19.23%**
St err	1.05	0.20	2.36%		0.79	2.59	-4.21%	0.79	2.45	1.84	2.54	7.69%
Corrected err	2.12	0.38			1.86	3.24		2.15	3.46	3.88	5.24	

Table 6: **Conditional models.**

The table reports the cross sectional regression estimation results for the consumption-CAPM model and two benchmark models: CAPM and the three factor model:

$$E[r_{i,t+1}] = \lambda_0 + \lambda\beta_i + \lambda_{term}\beta_{i,term}.$$

We use 25 futures contracts with varying sample period (see Table 3). In Panel A expected returns are measured as the historical means of the returns, while in Panel B yields-based expected returns are used. γ is the implied coefficient of risk aversion defined as $\frac{\lambda_c}{Var[\Delta c_{t+1}]}$. The first row reports the coefficient estimates. Fama-MacBeth standard errors are reported in the second row, and Shanken corrected standard errors are in the third row.

	conditional CCAPM					conditional CAPM				conditional Three factor model					
	λ_0	λ_c	λ_{term}	R^2 (R^2_{adj})	γ	λ_0	λ_{mkt}	λ_{term}	R^2 (R^2_{adj})	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{term}	R^2 (R^2_{adj})
Panel A : mean returns															
monthly															
Coeff	3.78	0.21	15.35	**23.02%**	169	4.09	-1.94	15.57	**23.48%**	3.93	-0.53	9.27	-0.99	17.80	**28.63%**
St err	1.55	1.19	5.99	16.02%		1.53	4.82	6.00	16.52%	1.56	5.13	8.58	8.51	6.36	14.36%
Corrected err	1.67	1.17	8.19			2.24	5.47	8.68		2.33	5.92	12.31	12.35	9.56	
quarterly															
Coeff	1.15	0.89	11.57	**58.70%**	505	3.88	-4.82	20.29	**29.48%**	3.97	-5.30	-5.03	9.06	16.96	**33.87%**
St err	1.24	0.20	6.07	54.95%		1.42	3.48	7.47	23.07%	1.45	3.56	4.99	6.63	8.21	20.65%
Corrected err	1.75	0.45	9.59			2.11	5.52	10.95	0.00	2.18	5.58	6.11	9.16	11.40	
yearly															
Coeff	0.56	0.65	38.58	**60.21%**	53	2.90	0.05	39.44	**39.29%**	2.92	-0.14	-0.19	-0.05	39.76	**39.32%**
St err	1.02	0.19	8.60	56.59%		1.04	2.85	10.53	33.78%	1.21	3.03	2.37	3.13	11.83	27.18%
Corrected err	1.89	0.33	22.90			2.18	3.81	21.88		2.21	4.02	3.57	6.41	19.87	
Panel B: yields															
monthly															
Coeff	0.66	-0.14	10.70	**21.94%**	-113	1.31	-6.78	11.80	**35.12%**	1.35	-5.72	1.78	-2.55	12.25	**36.39%**
St err	1.13	0.86	4.35	14.85%		1.01	3.20	3.98	29.22%	1.06	3.49	5.84	5.79	4.33	23.66%
Corrected err	1.98	1.45	8.58			2.59	5.46	8.70		2.58	5.68	13.83	14.00	9.12	
quarterly															
Coeff	-0.91	0.44	8.57	**36.43%**	249	0.37	-6.92	12.85	**45.21%**	0.56	-7.51	-8.05	4.53	9.70	**55.28%**
St err	1.08	0.18	5.29	30.65%		0.87	2.13	4.58	40.23%	0.83	2.04	2.86	3.80	4.70	46.34%
Corrected err	1.97	0.45	10.78			2.25	5.09	11.30		2.30	5.20	6.43	10.27	11.30	
yearly															
Coeff	-0.87	0.26	26.27	**36.26%**	22	0.10	-1.29	26.01	**31.78%**	-0.24	-1.26	-1.47	-3.91	25.56	**45.87%**
St err	0.98	0.18	8.30	30.46%		0.80	2.20	8.14	25.58%	0.83	2.09	1.64	2.15	8.15	35.04%
Corrected err	2.14	0.41	17.52			2.18	3.48	16.90		2.47	3.73	4.08	5.47	17.09	

Table 7: **Ultimate risk for unconditional models.**

The table reports the cross sectional regression estimation results for the consumption-CAPM:

$$E[r_{i,t+1}] = \lambda_0 + \lambda_1 \beta_i,$$

based on ultimate consumption risk for different horizons S:

$$\Delta c^S_{t+j} = \log\left(\frac{C_{t+j+S}}{C_t}\right).$$

We use 25 futures contracts with varying sample period (see Table 3). In Panel A expected returns are measured as the historical means of the returns, while in Panel B yields-based expected returns are used. γ is the implied coefficient of risk aversion defined as $\frac{\lambda_c}{Var[\Delta c^S_{t+1}]}$. We report Fama-MacBeth standard errors, and next to them Shanken corrected standard errors.

	Coefficient		St errors		Corr errors				
S	λ_0	λ_1	λ_0	λ_1	λ_0	λ_1	R^2	R^2_{adj}	γ
Panel A: mean returns									
monthly									
0	1.29	-0.20	1.27	1.27	1.51	1.17	**0.10%**	-0.04	-158
1	1.04	0.28	1.27	1.16	1.63	1.02	**0.25%**	-0.04	220
2	1.52	-0.63	1.18	0.91	1.73	1.08	**2.07%**	-0.02	-445
3	1.45	-0.63	1.15	0.99	1.77	1.13	**1.73%**	-0.03	-364
4	1.46	-0.82	1.12	1.00	1.79	1.19	**2.86%**	-0.01	-399
5	1.39	-1.14	1.07	1.00	1.80	1.26	**5.40%**	0.01	-473
6	1.37	-1.36	1.06	1.06	1.80	1.36	**6.60%**	0.03	-487
7	1.29	-1.47	1.06	1.15	1.81	1.44	**6.64%**	0.03	-463
8	1.25	-1.47	1.06	1.28	1.80	1.54	**5.40%**	0.01	-409
9	1.21	-1.40	1.07	1.40	1.79	1.62	**4.19%**	0.00	-348
10	1.14	-1.36	1.07	1.47	1.79	1.68	**3.58%**	-0.01	-302
11	1.14	-1.13	1.08	1.57	1.78	1.75	**2.19%**	-0.02	-225
12	1.14	-1.01	1.09	1.63	1.77	1.79	**1.65%**	-0.03	-183
quarterly									
0	-0.43	0.97	0.77	0.18	2.18	0.47	**55.23%**	0.53	545
1	-0.13	1.15	0.96	0.35	2.15	0.60	**32.52%**	0.30	394
2	0.42	1.05	1.05	0.51	2.03	0.70	**15.43%**	0.12	247
3	0.71	1.20	1.00	0.59	2.00	0.84	**15.20%**	0.12	206
4	1.02	1.11	1.00	0.66	1.92	0.89	**10.87%**	0.07	146
yearly									
0	-1.46	0.68	1.24	0.25	2.22	0.37	**23.78%**	0.20	56
1	0.05	0.60	1.05	0.32	2.09	0.47	**13.30%**	0.10	31
Panel B: yields									
monthly									
0	-0.97	-0.64	0.91	0.92	1.65	1.43	**2.07%**	-0.02	-515
1	-0.71	-1.04	0.90	0.82	1.94	1.19	**6.53%**	0.02	-826
2	-0.47	-1.61	0.75	0.58	2.07	1.19	**25.15%**	0.22	-1133
3	-0.59	-1.75	0.73	0.63	2.10	1.32	**25.07%**	0.22	-1010
4	-0.70	-1.90	0.70	0.63	2.09	1.42	**28.72%**	0.26	-922
5	-0.94	-2.06	0.66	0.61	2.01	1.50	**32.78%**	0.30	-849
6	-1.01	-2.26	0.65	0.65	1.99	1.61	**34.40%**	0.32	-811
7	-1.15	-2.41	0.65	0.70	1.96	1.73	**33.69%**	0.31	-760
8	-1.20	-2.56	0.66	0.80	1.95	1.91	**30.88%**	0.28	-714
9	-1.28	-2.65	0.67	0.89	1.93	2.06	**27.98%**	0.25	-657
10	-1.41	-2.69	0.68	0.94	1.90	2.18	**26.40%**	0.23	-599
11	-1.42	-2.67	0.70	1.02	1.89	2.32	**23.14%**	0.20	-533
12	-1.45	-2.66	0.71	1.06	1.88	2.43	**21.41%**	0.18	-481
quarterly									
0	-2.23	0.55	0.72	0.17	1.88	0.46	**31.22%**	0.28	308
1	-1.65	0.30	0.86	0.31	1.93	0.64	**3.98%**	0.00	104
2	-1.27	-0.05	0.86	0.42	1.93	0.83	**0.05%**	-0.04	-11
3	-1.29	-0.01	0.82	0.48	1.87	1.00	**0.00%**	-0.04	-2
4	-1.27	-0.16	0.80	0.53	1.86	1.12	**0.38%**	-0.04	-21
yearly									
0	-2.24	0.29	1.04	0.21	2.13	0.41	**7.23%**	0.03	23
1	-1.29	-0.01	0.86	0.26	2.01	0.55	**0.00%**	-0.04	0

Table 8: **Ultimate risk for conditional models.**

The table reports the cross sectional regression estimation results for the consumption-CAPM:

$$E[r_{i,t+1}] = \lambda_0 + \lambda_1 \beta_i + \lambda_{term} \beta_{i,term},$$

based on ultimate consumption risk for different horizons S:

$$\Delta c^S_{t+j} = \log\left(\frac{C_{t+j+S}}{C_t}\right).$$

We use 25 futures contracts with varying sample period (see Table 3). In Panel A expected returns are measured as the historical means of the returns, while in Panel B yields-based expected returns are used. γ is the implied coefficient of risk aversion defined as $\frac{\lambda_c}{Var[\Delta c^S_{t+1}]}$. We report Fama-MacBeth standard errors, and next to them Shanken corrected standard errors.

	Coefficient			Std errors			Corrected errors					
S	λ_0	λ_1	λ_{term}	λ_0	λ_1	λ_{term}	λ_0	λ_1	λ_{term}	R^2	R^2_{adj}	γ
Panel A: mean returns												
monthly												
0	3.73	0.39	14.79	1.45	1.15	5.52	1.77	1.21	7.98	**24.67%**	0.18	314
1	3.55	0.78	15.15	1.44	1.03	5.45	1.89	1.04	7.96	**26.18%**	0.19	620
2	3.86	0.06	14.57	1.40	0.86	5.73	1.87	1.08	7.62	**24.30%**	0.17	45
3	3.86	0.01	14.44	1.40	0.92	5.64	1.88	1.15	7.73	**24.28%**	0.17	4
4	3.88	-0.26	14.06	1.39	0.93	5.59	1.86	1.21	7.75	**24.55%**	0.18	-125
5	3.80	-0.57	13.58	1.39	0.94	5.57	1.81	1.29	7.74	**25.51%**	0.19	-233
6	3.76	-0.74	13.38	1.39	1.00	5.56	1.80	1.39	7.77	**26.09%**	0.19	-264
7	3.72	-0.84	13.39	1.39	1.07	5.52	1.79	1.47	7.86	**26.35%**	0.20	-266
8	3.74	-0.79	13.58	1.40	1.19	5.53	1.79	1.59	7.93	**25.75%**	0.19	-220
9	3.75	-0.72	13.78	1.40	1.29	5.52	1.79	1.68	7.99	**25.33%**	0.19	-179
10	3.73	-0.70	13.88	1.41	1.35	5.50	1.79	1.76	8.03	**25.19%**	0.18	-156
11	3.78	-0.49	14.10	1.41	1.43	5.50	1.79	1.84	8.06	**24.69%**	0.18	-99
12	3.79	-0.45	14.18	1.41	1.48	5.48	1.80	1.90	8.08	**24.60%**	0.18	-81
quarterly												
0	1.38	0.81	10.81	1.06	0.18	4.69	1.60	0.42	8.85	**63.94%**	0.61	451
1	2.33	0.95	15.72	1.13	0.30	5.00	1.87	0.56	9.76	**53.44%**	0.49	326
2	3.07	0.92	18.01	1.18	0.43	5.38	1.99	0.70	10.13	**43.93%**	0.39	217
3	3.30	0.99	17.61	1.17	0.51	5.49	1.98	0.83	9.93	**42.21%**	0.37	169
4	3.60	0.88	17.92	1.18	0.56	5.65	2.00	0.89	9.92	**38.86%**	0.33	116
yearly												
0	0.56	0.65	38.58	1.02	0.19	8.60	1.91	0.33	22.78	**60.21%**	0.57	53
1	2.02	0.60	39.62	0.93	0.24	9.46	2.08	0.45	22.03	**51.78%**	0.47	31
Panel B: yields												
monthly												
0	0.81	-0.21	10.81	1.04	0.83	3.97	1.98	1.49	8.57	**26.78%**	0.20	-171
1	1.01	-0.69	10.37	1.03	0.74	3.89	2.11	1.28	8.82	**29.39%**	0.23	-552
2	0.88	-1.21	8.46	0.91	0.56	3.74	2.15	1.34	9.45	**39.24%**	0.34	-849
3	0.88	-1.36	8.76	0.90	0.60	3.64	2.17	1.46	9.35	**40.67%**	0.35	-786
4	0.81	-1.55	8.75	0.87	0.58	3.49	2.17	1.55	9.27	**44.55%**	0.40	-752
5	0.56	-1.70	8.45	0.85	0.57	3.41	2.12	1.64	9.29	**47.42%**	0.43	-700
6	0.48	-1.87	8.33	0.84	0.61	3.38	2.11	1.74	9.23	**48.61%**	0.44	-672
7	0.40	-2.01	8.53	0.85	0.65	3.36	2.10	1.86	9.13	**48.71%**	0.44	-635
8	0.40	-2.12	8.73	0.86	0.74	3.42	2.11	2.03	9.07	**46.68%**	0.42	-592
9	0.38	-2.20	9.02	0.88	0.81	3.45	2.11	2.17	8.99	**45.03%**	0.40	-546
10	0.31	-2.26	9.23	0.89	0.85	3.46	2.10	2.29	8.94	**44.39%**	0.39	-501
11	0.36	-2.25	9.52	0.90	0.91	3.51	2.11	2.43	8.89	**42.42%**	0.37	-448
12	0.38	-2.28	9.76	0.90	0.95	3.51	2.11	2.54	8.85	**41.85%**	0.37	-410
quarterly												
0	-0.41	0.38	10.84	0.97	0.17	4.29	1.88	0.46	9.10	**46.67%**	0.42	214
1	0.59	0.12	14.32	1.01	0.27	4.46	2.16	0.65	9.22	**34.65%**	0.29	42
2	0.93	-0.15	14.92	0.96	0.35	4.38	2.28	0.87	9.68	**34.60%**	0.29	-36
3	0.92	-0.20	15.04	0.94	0.40	4.39	2.28	1.04	9.72	**34.75%**	0.29	-34
4	0.92	-0.35	15.20	0.91	0.43	4.35	2.30	1.18	9.83	**35.94%**	0.30	-47
yearly												
0	-0.87	0.26	26.27	0.98	0.18	8.30	2.14	0.41	17.45	**36.26%**	0.30	22
1	0.05	-0.01	26.72	0.85	0.22	8.69	2.23	0.57	17.58	**30.06%**	0.24	-1

Table 9: **Consumption betas at different horizon.**

This table reports consumption betas estimated by time-series regression:

$$r_{i,t+1} = \alpha_i + \beta_{i,c^S} \Delta C^S_{t+1} + \epsilon_{i,t+1}.$$

based on ultimate consumption risk for different horizons S:

$$\Delta c^S_{t+j} = \log\left(\frac{C_{t+j+S}}{C_t}\right).$$

We use 25 futures contracts with varying sample period (see Table 3).

Futures \Horizon (S)	0	1	2	3	4
Wheat	0.07	0.14	0.06	-0.06	-0.13
Corn	1.18	0.25	0.07	-0.07	-0.14
Oats	-1.62	0.17	0.48	0.36	0.23
Soybean	2.20	0.73	0.37	0.15	0.03
Soybeans Oil	-1.29	-0.77	-0.55	-0.42	-0.35
Soybean meal	5.64	2.03	1.06	0.57	0.31
Live cattle	1.73	0.80	0.51	0.31	0.20
Feeder cattle	2.13	1.08	0.62	0.37	0.26
Live hog	2.87	1.09	0.57	0.35	0.24
Porl Bellies	2.29	1.22	0.64	0.44	0.37
Crude Oil	6.88	0.54	-0.08	-0.01	-0.10
Heating Oil	7.26	1.75	0.68	0.35	0.16
Unleaded Gasoline	9.75	2.00	0.40	0.20	0.00
Gold	-1.55	-0.22	-0.20	-0.19	-0.15
Silver	3.03	1.74	0.70	0.27	0.12
Platinum	2.71	1.65	0.87	0.40	0.22
Copper	4.56	1.11	0.10	-0.08	-0.08
Coffee	3.70	1.40	0.97	0.60	0.44
Sugar	-10.74	-4.28	-2.12	-1.42	-1.05
Cotton	3.03	0.86	0.12	-0.09	-0.15
S&P 500	0.97	1.19	0.78	0.49	0.39
Japanese Yen	0.28	0.50	0.36	0.24	0.20
British Pound	-1.33	-0.41	-0.22	-0.16	-0.12
Candian $	-0.43	-0.12	-0.06	-0.03	-0.01
Swiss Frank	-1.16	-0.01	0.07	-0.01	-0.02

Table 10: **Ultimate risk for investment growth models.**

The table reports the cross-sectional regression estimation results for the investment growth model:

$$E[r_{i,t+1}] = \lambda_0 + \lambda\beta.$$

For the unconditional model (Panel A) the vector β consists of the following two sets of betas:

$$\beta_{i,nr} = \frac{Cov\left[r_{i,t+j}, \Delta i_{nr}^S\right]}{Var\left[\Delta i_{nr}^S\right]},$$
$$\beta_{i,r} = \frac{Cov\left[r_{i,t+j}, \Delta i_{r}^S\right]}{Var\left[\Delta i_{r}^S\right]},$$

where Δi_{nr} is the growth rate of the non-residential investments, and Δi_r is the growth rate in the residential investments. The conditional model (Panel B) contains additionally the conditional beta $\beta_{i,term}$. We use 25 futures contracts with varying sample period (see Table 3). For each model we use the historical means of the returns (top block of each panel), and yield-based expected returns (bottom block of each panel).

	Coefficient				Std errors					
S	λ_0	λ_{nr}	λ_r	λ_{term}	λ_0	λ_{nr}	λ_r	λ_{term}	R^2	R^2_{adj}
					Panel A: Unconditional model					
					mean returns					
					quarterly					
0	-0.03	5.26	-4.26		0.85	1.37	2.51		**53.48%**	0.49
1	-0.72	7.01	-4.06		0.91	1.83	2.57		**56.82%**	0.53
2	-0.86	8.51	-4.73		0.92	2.30	2.62		**58.17%**	0.54
3	-1.11	9.90	-5.65		0.98	2.89	3.16		**55.32%**	0.51
4	-1.44	11.57	-5.96		1.06	3.62	3.77		**51.81%**	0.47
					yearly					
0	0.95	3.05	-3.31		1.02	1.56	2.21		**22.41%**	0.15
1	0.00	3.58	-3.14		1.07	1.95	2.13		**20.46%**	0.13
					yields					
					quarterly					
0	-2.04	3.37	-4.20		0.57	0.92	1.68		**57.58%**	0.54
1	-2.27	3.71	-5.37		0.59	1.19	1.67		**62.85%**	0.59
2	-2.26	4.05	-6.16		0.60	1.50	1.71		**63.73%**	0.60
3	-2.40	4.44	-7.43		0.64	1.88	2.06		**61.41%**	0.58
4	-2.56	4.83	-8.53		0.69	2.35	2.45		**58.86%**	0.55
					yearly					
0	-0.78	0.60	-3.81		0.79	1.21	1.72		**19.31%**	0.12
1	-1.38	0.91	-4.56		0.76	1.39	1.52		**30.13%**	0.24
					Panel B: Conditional models					
					mean returns					
					quarterly					
0	0.86	4.70	-4.00	5.62	1.43	1.57	2.56	7.29	**54.76%**	0.48
1	0.37	6.26	-3.75	6.63	1.44	1.98	2.59	6.72	**58.74%**	0.53
2	0.18	7.60	-4.47	6.10	1.46	2.52	2.65	6.69	**59.77%**	0.54
3	0.14	8.61	-5.34	7.18	1.54	3.13	3.16	6.81	**57.56%**	0.52
4	0.08	9.81	-5.62	8.46	1.63	3.86	3.74	6.92	**55.02%**	0.49
					yearly					
0	2.54	1.13	2.11	44.28	1.06	1.54	2.77	16.15	**42.87%**	0.35
1	2.17	2.08	0.59	38.24	1.19	1.77	2.26	13.34	**42.83%**	0.35
					yields					
					quarterly					
0	-1.76	3.19	-4.12	1.75	0.97	1.06	1.73	4.93	**57.83%**	0.52
1	-1.80	3.39	-5.24	2.82	0.95	1.30	1.71	4.43	**63.55%**	0.58
2	-1.76	3.61	-6.03	2.92	0.97	1.66	1.74	4.41	**64.47%**	0.59
3	-1.72	3.74	-7.27	3.89	1.01	2.06	2.08	4.47	**62.75%**	0.57
4	-1.69	3.82	-8.34	4.85	1.06	2.52	2.44	4.51	**61.00%**	0.55
					yearly					
0	0.14	-0.51	-0.66	25.71	0.89	1.29	2.32	13.53	**31.15%**	0.21
1	-0.42	0.24	-2.89	17.04	0.95	1.41	1.80	10.62	**37.76%**	0.29