Long-run expected consumption and volatility risk, and the cross-section of asset returns

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This paper builds on the Long-Run Risks Framework in the quest of explaining the true nature of risk that drives asset prices. Instead of modeling expected consumption as in past research, we use the forward-looking Michigan Consumer Sentiment Index to proxy innovations in the agent's beliefs about expected consumption growth. We use monthly data from 1979.03-2011.12 in our cross-sectional tests using the Fama & Macbeth procedure on portfolios sorted on value and size, short-term reversal and size, as well as long-term reversal and size. In line with theory, our findings suggest that an assets that covaries positively with changes in beliefs about expected consumption growth requires a risk premia. Growth in economic uncertainty, defined as innovation in expected consumption volatility is negatively priced in our tests which confirm the general findings of the Long-Run Risks literature.

Keywords: asset pricing, expected consumption, cross-section of returns, Long-Run Risk, Consumer Sentiment Index

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1. Introduction

Why do returns vary across assets? This question has puzzled practitioners and scholars alike as long as financial markets have been around. The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Black (1972) addressed that question and has since shaped the way people have been thinking about risk across assets. The CAPM makes the simplifying assumption that the only source of wealth that exists for investors is the market (Cochrane, 2005b). This implies that an asset's expected return is a function of its covariance with the market portfolio and that the return of the market is all that is needed to describe the cross-section of asset returns. Since the model denies income and other sources of "wealth", it is not surprising that the CAPM has performed poorly in empirical tests, particularly in later years.

The consumption based asset-pricing model (CCAPM) of the type studied by Rubinstein (1976), Lucas (1978) and Grossman & Shiller (1981) tried to answer the question by measuring the risk of an asset by its payoff's covariance with per capita consumption growth. Also this model has failed to withstand empirical tests, but sparked a branch of later models that has tried to link consumption growth to asset prices.

Since the introduction of the two cornerstones of asset pricing above, several models have been suggested in the quest of explaining the cross section of asset returns. The Fama and French (1992) three factor model (FF3F) is probably the most famous one. In addition to the market factor, they add two factors; SMB that captures the "size" effect observed in the stock market and HML that captures the "value" effect. Researchers such as Fama and French have been reasonably successful in explaining the cross section with these special portfolios, but the real challenge is to understand the macroeconomic risks that underlie these factors.

In the article "*Financial Markets and the Real Economy*", (Cochrane J. , 2005a) notes that even though quite a lot of work has been done in trying to explain the cross-section of asset returns, the work has barely begun. "*In sum, the program of understanding the real, macroeconomic risks that drive asset prices (or the proof that they do not do so at all) is not some weird branch of finance; it is the trunk of the tree. As frustratingly slow as progress is, this is the only way to answer the central questions of financial economics, and a crucial and unavoidable set of uncomfortable measurements and predictions for macroeconomics.*" (p. 6). Our ambition is to further extend this field of research and explore the fundamental economic determinants of marginal value of wealth that drive asset prices. If we could better understand the marginal value of wealth that drives asset markets, it can help us answer the central question in finance of whether asset markets are efficient or not, a question that can never be fully understood by using portfolios on the right hand side. For macroeconomists, understanding what drives marginal value of wealth in asset markets provides a key ingredient in the central equation of savings and investment, the allocation of consumption and investment across time and states of nature.

One recent strand of promising research within this field is the Long-Run Risks literature (Bansal & Yaron, 2004; Epstein & Zin, 1989; Bansal, Khatchatrian, & Yaron, 2005; Tédongap, 2010; Ang, Hodrick, Zhang, & Xing, 2006; Lettau, Ludvigson, & Wachter, 2008). In this model, the representative agent is assumed to have Epstein-Zin Weil preferences that separate the elasticity of intertemporal substitution from being the inverse of relative risk aversion. This salient feature allows innovations in expected consumption growth and volatility to enter the pricing kernel.

Past research within the Long-Run Risk literature have modelled the dynamics of expected consumption growth using historic data, or sometimes even more simply, just used actual consumption data of future periods. In this paper, we capture innovations in the investor's *long-term consumption growth expectations* directly through changes in the University of Michigan's Consumer Sentiment Index (CSI), thus extending the Long-Run Risk literature by capturing innovations in expected consumption growth directly through a proxy, thus forming an *expected consumption factor*. Given that innovations of the CSI is a good proxy for changes in beliefs about expected consumption growth, we are able to more directly capture larger innovations and dispersion in expected consumption growth within periods, compared to past research within the Long-Run Risk literature.

The general findings within the Long-Run Risks framework suggest that assets that covary negatively with innovations in beliefs about consumption volatility (changes in beliefs about economic uncertainty) require a risk premia. We measure innovations in volatility of the CSI to capture changes in economic uncertainty, and thus form an *expected consumption volatility factor.* This factor captures innovations in economic uncertainty by measuring dispersion in the agent's expected growth rate of consumption. The more uncertain the times, the more dispersion we expect in agent's beliefs about future consumption growth. We specify two non-parametric and one parametric measurement of innovations in expected consumption volatility.

With these two new sets of factors we construct a 4-factor model, including; the market return, consumption growth, innovations in expected consumption growth and (three different) specifications of innovations in expected consumption volatility.

This paper naturally starts with an introduction to consumption-based asset pricing before departure into the Long-Run Risk framework. This is followed by an extensive walk-through of the logic behind each of our factors and their pricing implications in the Long-Run Risk framework. Finally, we empirically test our model in the cross-section of asset returns.

2. Literature review and the story of our factors

2.1 Background

The transcendence to understanding the real nature of macroeconomic risks that drive risk premia in asset markets goes beyond any constructed portfolio-based factor model. "*The differences in expected returns across assets are determined by differences in the asset's exposure to systematic risk*". This short sentence by Da (2009, p. 923) sums up the essence of asset pricing. It is all about identifying the right measures of "bad times", in other words, identify the drivers of marginal value of wealth in order better understand low prices as a compensation for an asset's tendency to payoff poorly in "bad times". (Cochrane J. , 2005a). This quest has confounded finance scholars for the past decades. Most of the past research in the field has tried to capture risk by attributing the variation in returns to differences in covariance between an asset's payoff and growth of the agent's consumption or with the market portfolio. The first part of this chapter discusses the theory and past research related to CCAPM. Then we extend into the Long-Run Risks framework and after a discussion of the long-run components, we present our measures of these factors. We include the market return as a fourth factor and the rationale for this is discussed in one of the subsequent sections.

2.2 The consumption factor

In the CCAPM an asset's expected return should be determined by its covariance with the investor's consumption stream. This view is based on the notion that if an asset's payoff is high when the investor's consumption is low, that is in "bad times" it works as a hedge for the investor. Therefore, the agent prefers (values more) this asset compared to an asset that pays off in "good times" but not in "bad times" when consumption is critical. The standard CCAPM was first studied by Rubinstein (1976), Lucas Jr (1978) and Grossman & Shiller (1981) and has since been scrutinized thoroughly. Over the years, it has been shown that what theoretically seemed like a comprehensive model has not turned out to work well empirically. In the textbook statement of the *equity premium puzzle*, Mehra & Prescott (1985) first introduced the discrepancy between the intuitive CCAPM and what was observed in reality. The puzzle states that under standard assumptions, given the observed low volatility of consumption, the risk premium of stocks is too high. The key question has since been whether the problem lies in the data, or in the model. Despite the lack of success of the standard consumption based model, several alternations have proved more successful.

In the following section the basic CCAPM is first introduced as presented by Cochrane (2005b), followed by research on how well the CCAPM has stood up empirically, as well as our intuition for including it as a risk factor.

2.2.1 The basic Consumption-based asset pricing model (CCAPM)

Starting with the representative agent's intertemporal choice problem consisting of two periods, the agent's choice is modelled in the following way:

$$U(c_t, c_{t+1}) = u(c_t) + \beta E_t[\,u(c_{t+1})]$$

where c is consumption, β is the agent's impatience for delaying consumption, E is expectations and u is utility. The utility function is modelled in a power utility form:

$$u(c_t) = \frac{1}{1-\gamma} c_t^{1-\gamma}$$

The limit as $\gamma \to 1$ is

$$u(c) = ln(c)$$

The agent's utility function is increasing and concave, which reflects a desire for more consumption, while the utility is decreasing with each extra unit of consumption. The investor's objective is to maximize:

$$max\ u(c_t) + E_t[\,\beta u(c_{t+1})]$$

The investor can sell as much as she wants θ of a future payoff x_{t+1}, at the price today p_t, given the original level of endowment e under the constraints:

$$c_t = e_t - p_t\theta \text{ , and } c_{t+1} = e_{t+1} + x_{t+1}\theta$$

This leads to the investor's first order condition that determines her optimum investment decision at time *t* and thus the price:

$$p_t u^{\prime}(c_t) = E_t\left[\beta\, u^{\prime}(c_{t+1}) x_{t+1}\right]$$

where β is called the *subjective discount factor* and captures impatience. At the investment decision in time *t*, the representative agent chooses how much to consume and how much to save/invest based on her expected marginal utility benefit from investing the dollar in an asset at time t, selling it at time *t+1*, and consuming the proceeds. The price at time *t* is given by:

$$p_t = E_t\left[\beta\, \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1}\right]$$

where

$$m_{t+1} = \beta\, \frac{u'(c_{t+1})}{u'(c_t)}$$

is the *stochastic discount factor,* also called *the marginal rate of substitution.* Since we assume that the investor prefers more to less, but that the utility from one more unit of consumption is decreasing, we have $u' > 0$ and $u'' < 0$. High future consumption (good times) equals low marginal utility, and low future consumption equals high marginal utility. The investor prefers a steady consumption stream over time and across states. Cochrane (2005b) denotes the investor's marginal utility "hunger", and states that "*the variance of the return or payoff is irrelevant and does not measure risk or generate a risk premium, only the covariance of the return with "hunger" matters*" (p.3).

The price of an asset at the time of the investment decision in time t satisfies (implied by no arbitrage) the basic pricing equation for absolute pricing:

$$p_t = E_t\ (m_{t+1}\ x_{t+1})$$

This implies that all assets have the same stochastic discount factor and that the only thing that impacts its price is its "riskiness" for the agent. Since expected discounted returns should always equal 1, we write the basic pricing equation for returns:

$$1 = E\left(mR^i\right)$$

Using covariance decomposition and substituting in the equation for the risk free rate gives:

$$E\left(R^i\right) - R^f = -\frac{cov\left[u'\ (c_{t+1}), R^i_{t+1}\right]}{E\left[u'\ (c_{t+1})\right]}$$

The expected return of an asset in the CCAPM is determined by the risk free rate plus a risk correction for the covariance of the asset's return with consumption growth. The takeaway from this formal presentation is that in the CCAPM, the only factor determining a security's risk for the representative agent is the covariance of the security's return with per capita consumption growth. The more negatively the asset's payoff is correlated with growth in marginal utility (the more positively the asset is correlated with growth in consumption) the lower the price of the asset and the higher the expected return. In other words, the investor requires a risk premia to hold an asset with a low payoff in bad times that further deteriorates the ability to consume. Conversely, an asset with a negative covariance with consumption growth will be more valuable since it shields the investor against a drop in consumption. Investors are therefore willing to pay more for that asset.

2.2.2 Empirical evaluations of CCAPM

If the CCAPM was to hold, and consumption growth was the only risk factor agents cared about, then all assets should be priced in the cross-section depending on the assets covariance with consumption growth. However, as mentioned before, with Mehra and Prescott (1985), academia started to question whether the relationships presented in the previous section holds empirically. Mehra and Prescott concluded that in order to explain the much higher returns of stocks compared to government bonds, investors must have an extremely high relative risk aversion for the CCAPM relationship to hold. They show that the difference in the covariance of stock returns with consumption growth, and bond returns with consumption growth, is not large enough to explain the difference in risk premiums without an unrealistically high risk aversion. Their main finding is that the difference in expected real returns, the equity premium, is less than 0.35 % according to their analytical formula, far below the equity premium of more than 6% that the empirical data shows.

Later empirical evidence has continued to find little support for CCAPM. Hansen and Singleton (1983) reject the CCAPM in their statistical tests. Mankiw & Shapiro (1986) even found that CAPM performs better than the CCAPM in explaining the cross section of asset returns, while Breeden, Gibbons, & Litzenberger (1989) found that CCAPM performed about as well as the standard CAPM. Hansen & Jagannathan (1997) finds that the pricing errors from the CCAPM are rather large.

2.2.3 Consumption is still a risk factor

The failure of the CCAPM is not qualitative. There is a positive relation between an asset's expected return and its covariance with consumption growth. The problem is instead quantitative; the risk premium of assets compared to bonds is too high to be explained by a stochastic discount factor based solely on consumption growth. It is not volatile enough.

Over the years there have been many suggested solutions to the issues related to the CCAPM. Alternations such as the *habit formation model* (Campbell & Cochrane, 1999), models with heterogeneous agents (Campbell & Mankiw, 1989), the *prospect theory model* (Benartzi & Thaler, 1995) and introduction of frictions and transaction costs (Heaton & Lucas, 1996) have all managed to improve the extent to which consumption manages to capture the equity premia.

Others have assumed that the problems lies in the measure of consumption and used alternative measures such as garbage consumption (Savov, 2011), durables (Yogo, 2006) or luxury goods (Yogo, Ait-Sahalia, & Parker, 2004), which have performed slightly better than the standard measure of real per capita NIPA consumption growth in the cross-section. Also, by carefully adjusting the measurement of consumption growth to account for the fact that consumption is a flow measure, such as using fourth quarter observations to calculate annual growth has shown to improve the performance of the CCAPM.

In general, the CCAPM alone has failed to explain the cross section of returns. Researchers seem to agree on that there must be systematic risk factors beyond aggregate consumption growth that matters. In the Long-Run Risk framework we include consumption growth as a factor to capture short-term risk. Past research has shown that it indeed capture some of the systematic risk that investors face, even though the relationship is weak.

In order to introduce other factors the assumptions underlying CCAPM cannot hold. A promising strand of research are long-run risk models, that assume that agents, in addition to consumption risk, care about shocks to expected consumption growth and volatility, with large empirical pricing implications in the cross-section.

2.3 Expected consumption factor

In the following section, we present theory and research around Long-Run Risk followed by a description of how and why we proxy innovations in expected consumption growth through the

Consumer Sentiment Index (CSI). A detailed review of the CSI and its relation to consumption and the stock market is also included in this section.

2.3.1 Introduction to Long-Run Risks

As previously discussed, much of past literature has shown that contemporaneous consumption growth does not fully explain the differences in excess returns across assets. The asset pricing literature has reached something of a consensus that differences in expected returns must also stem from other sources, such as time varying risk aversion or more advanced models of economic behaviour.

One direction in academia has proposed that not only consumption growth in the next period matters, but also in many periods to come. Parker and Julliard (2005) studied the Fama and French size and book-to-market portfolios and re-evaluated the CCAPM using what they termed *"Ultimate risk",* defined as the covariance of an asset's payoff with consumption growth over many following quarters. They were of the opinion that it is not only risk related to contemporaneous consumption growth that matters, but also to *future* growth. Parker and Julliard(2005) proposed that expected returns are given by:

$$E\left[R_{i,t+1}^{e}\right] = -\frac{Cov\left[m_{t+1}^{s}, R_{i,t+1}^{e}\right]}{E\left[m_{t+1}^{s}\right]},$$

This only differs from the CCAPM set-up in that risk is measured by the covariance of an asset's return at $t+1$, and the change in marginal utility from t to $t+1+S$, where S is the time horizon. Parker and Julliard find strong empirical results supporting this framework. While contemporaneous consumption growth explains a very small part of the variation in expected returns, their risk measure manages to explain between 44 % and 73 % of the variation between portfolios.

In a quite simple framework Parker and Julliard's study highlights the importance of risk over the long run. However, the authors of this paper disagree with the idea that the expected return of an asset is decided by its return's covariance with *observed* long-run consumption growth, and are instead of the opinion that the covariance of the return with *expected* long-run consumption growth is a more important driver of asset prices. This is because at the day of the valuation of the asset, future consumption growth is not *known*, only *expected* by the agent, and as we will describe later in this paper, when we extend the horizon of expectations, forecasted dynamic variables only rarely coincide with what is later realized. Hence it follows that the expected consumption growth rate does rarely coincide with the (later) realized growth rate of consumption. In other words, we are more certain about the state of the economy tomorrow than five years from now (these dynamics are further explained in section 2.3.4.1).

The Long-Run Risks (LRR) model of Bansal & Yaron (2004) is a more extensive framework than the one by Parker & Julliard, focusing on two long-run risks channels: long-run fluctuations in *expected consumption growth* and long-run innovations in *expected consumption volatility*. The LRR model is based on four important assumptions. First, that there exists a predictable component of consumption growth. Second, that there needs to be a predictable component of consumption volatility. Third, that consumption and dividend are not the same. The stock market is a claim to dividend, which is more volatile than consumption, but they are still correlated and have the same predictable component. Lastly, that the representative agent in the framework is assumed to have *Epstein-Zin Weil preferences*.

2.3.2 Epstein-Zin Weil Preferences

The assumptions mentioned above are important and particularly the Epstein-Zin Weil preferences need further explanation. In the standard CCAPM framework with power utility, the investor is assumed to have CES time additive expected utility preferences. That type of preferences implies that the elasticity of intertemporal substitution (EIS) is simply the reciprocal of the relative risk aversion (RRA), a highly constraining feature of the framework since only aggregate consumption growth can enter the pricing kernel. For the standard CCAPM to fit the data, a very high RRA has to be assumed, which due to the restriction implies a low EIS. A low EIS means that the investor is very reluctant to defer consumption (save) to consume at a later state (Mehra & Prescott, 1985), something that we do not observe in reality. A low EIS thus implies a high-risk free rate in equilibrium, which is what Weil (1989) named *the risk free rate puzzle*. In order to come around this problem Weil also brought up a parametric class of Kreps-Porteus non-expected utility preferences, which was first introduced by Epstein and Zin (1987):

$$U_t = \left\{(1-\beta)(C_t)^{\frac{1-\gamma}{\theta}} + \beta E_t\left[U_{t+1}^{1-\gamma}\right]^{\frac{1}{\theta}}\right\}^{\frac{\theta}{1-\gamma}} \text{where } \theta = \frac{1-\gamma}{1-\frac{1}{\varphi}}$$

Here φ is the EIS, γ the RRA, β the rate of time preference, C is consumption. These are recursive, non-state separable, so the marginal utility of consumption in one state is not unaffected of what happens in another state. The investor maximizes her lifetime utility subject to the budget constraint:

$$W_{t+1} = (W_t - C_t)R_{W,t+1}$$

Where $R_{W,}$ is the return to the unobserved total wealth W, and W is a claim to future consumption. The current period utility is determined by a combination of current consumption and the certainty equivalent of future utility. Cochrane (2005b) mentions two advantages with a *non-state-separable* utility set-up. First, it separates the RRA from the EIS in the sense that one is not the reciprocal of the other as in the power utility case. The separation of RRA from EIS allows for shocks to innovations in expected consumption growth and volatility to enter the pricing kernel. The second advantage is that the first-order condition can be expressed so that both current consumption growth and the wealth portfolio return enter the marginal utility of wealth, allowing for the inclusion of stock returns alongside consumption growth.

2.3.3 Long run risks- The framework

The utility preferences presented in the previous section allow us to define the following stochastic discount factor:

$$m_{t+1} = \delta \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} \left(\delta \frac{\frac{W_{t+1}}{C_{t+1}}}{\frac{W_t}{C_t} - 1}\right)^{\theta-1}$$

Where W_t is total wealth, C is consumption, γ the parameter of risk aversion, δ the subjective discount factor and $= \frac{1-\gamma}{1-\frac{1}{\varphi}}$. (In the special case where $\gamma = \frac{1}{\varphi}$, then θ = 1 and only aggregate consumption enters the stochastic discount factor.). A log linearization of the pricing kernel is given by:

$$m_{t+1} \approx k - \gamma \, \Delta \, C_{t+1} - (1-\theta) \, \Delta \, z_{t+1}$$

where z_t is the log wealth-consumption ratio. The excess returns are determined by the covariance between returns and log consumption growth (short-run risk), and between returns and growth in the log wealth-consumption ratio (long run risk). We identify innovations in beliefs about the conditional mean and volatility of expected consumption growth as two variables that affect the wealth-consumption ratio and thus asset prices. Boguth and Kueh(forthcoming) points out that if the EIS is larger than the inverse of the relative risk aversion, the agent prefers intertemporal risk to be resolved sooner than later, and requires a higher premia for assets that load more on innovations in expected consumption growth (positive price of risk), and requires a higher risk premia for assets that covaries negatively with innovations in excepted consumption volatility, that is an asset with a negative payoff when times become more uncertain (negative price of risk).

What is the intuition behind this? Investors have a view upon the future growth rate of the economy and if that view is lowered through bad news it is reflected in asset prices. An asset with a payoff that has a negative covariance with expected consumption growth will have a positive payoff when expectations about the future state of the economy falls (negative innovations in expected consumption growth). This asset will be preferred and more valuable to the investor who will be willing to pay a higher price for that asset, compared to an asset with opposite characteristics (positive covariance with innovations in expected consumption growth). Also, investors prefer certainty in their view upon the future states of the economy, hence investors will prefer an asset with a payoff that rises when times become more uncertain and will be willing to pay a premium for that asset compared to an asset with a payoff that falls a lot when times become more uncertain.

Expected consumption growth in the LRR framework is an unknown variable. Given that we find a good proxy for expected consumption growth, then from an intuitive perspective, we have a series of expectations taken at different points in time. To show how a direct proxy of expected consumption growth differs from other studies in the Long-Run Risks framework, we believe it is of interest to look at how Bansal and Yaron (2004) and Bansal, Kiku, & Yaron (2012) model the dynamics of consumption growth and dividend growth:

$$\Delta C_{t+1} = \mu_c + X_t + \sigma_t \eta_{t+1}$$
$$X_{t+1} = \rho X_t + \varphi_e \sigma_t e_{t+1}$$
$$\sigma_{t+1}^2 = \bar{\sigma}^2 + v(\sigma_t^2 - \bar{\sigma}^2) + \sigma_w W_{t+1}$$
$$\Delta d_{t+1} = \mu_d + \phi X_t + \pi \sigma_t \eta_{t+1} + \varphi \sigma_t u_{d,t+1}$$

where ΔC_{t+1} and Δd_{t+1} are growth rates of consumption and dividends respectively. $\mu_c + X_t$ is the conditional expectation of consumption growth, where X_t is a small but persistent component that captures long run risks in consumption growth. Expected consumption is here the outcome of an autoregressive model and will be highly persistent. It will therefore have limited ability to capture the true shifts in investor expectations[1].

Bansal & Yaron then derive a solution to the model[2], but what is interesting for the sake of this paper is the asset pricing implications of the model implies which consist of three sources of risk. The innovation to the pricing kernel is solved to be

$$m_{t+1} - E_t(m_{t+1}) = -\lambda_\eta \sigma_t \eta_{t+1} - \lambda_e \sigma_t e_{t+1} - \lambda_w \sigma_w W_{t+1}$$

where the $\lambda' s$ represent the market price of risk for consumption shocks λ_η , expected consumption growth shocks λ_e, and volatility shocks λ_w, respectively. These are the risk factors that we want to capture in our model (we also add the market factor as explained later in the paper). The equity premium in their model is solved to be:

$$E_t\left(r_{m,t+1} - r_{f,t}\right) = \beta_{m,e}\lambda_{m,e}\sigma_t^2 + \beta_{m,w}\lambda_{m,w}\sigma_w^2 - 0.5Var(r_{m,t+1})$$

This model sparked a strand of studies focusing on risks in the long run. Bansal & Yaron (2004), Hansen, Heaton, & Li (2008) and Bansal, Dittmar, & Lundblad (2005), Tedongap (2010) and Boguth & Kuehn (forthcoming) are some of the studies on the frontline of the Long-Run Risks framework.

2.3.4 How long-run risk is captured in our model

In contrast to the standard LRR framework shown above where the variables are outcomes from an evolving stochastic process, we propose another approach to capture innovations in expected

[1] Boguth and Kuehn(forthcoming) and Letta, Ludvigson and Wachter(2008) assumes that (expected) consumption dynamics follows Markov chains with unobservable states (Boguth & Kuehn, forthcoming; Lettau, Ludvigson, & Wachter, 2008). These model dynamics also result in high persistence and low dispersion in expected consumption.
[2] For a complete walk-through of the LRR model please refer to Ravi Bansal's chapter in the *Hanbook of the equity risk premium* (2008) or Bansal & Yaron (2004)

consumption growth. The authors of this paper felt that that a model based on observable measures rather than on a structural framework would be interesting. The LRR framework is very abstract, so by finding variables to proxy the risk factors mentioned above we aim to capture the same risk in a more concrete manner. The problem that we then face is that expected consumption growth is a forward-looking variable and as such cannot be directly observed in any available data today. Expected consumption growth should intuitively be linked to economic growth prospects just like Bansal & Yaron (2004) points out. The question is how to best capture investors' view on future economic growth prospects.

Following the LRR framework, we formulate two factors, one that captures the risk premia associated with innovations in the agent's expectation of future consumption growth and one that captures the risk related to innovations in economic uncertainty. The direct measurement of the dynamics of expected consumption growth in this paper, (the growth of the CSI) is an important extension to past research since we do not rely on modelling growth in expected consumption based on historical data. Instead, we capture the forward-looking measurement directly and irrespective of its past. This is important because it gives us the opportunity to capture large innovations in beliefs *between periods,* which is especially important in times when views about the future economy changes rapidly.

2.3.4.1 Uncertainty of a dynamic variable - Expected consumption growth

The dynamics of expected consumption growth are important and needs further explanation. The variable can be seen as a forecast and as such the forecasting error is important to address. Many economic variables such as income, interest rates, consumer expenditures and inflation are highly dynamic, characterized by time dependence and persistency (Ericsson, 2001).

Unlike static variables, the forecast horizon of consumption, income and other variables is affected by the forecast horizon. Feigenbaum and Geng(2008, p. 6), emphasize this intuition *"intuitively then, for a given income process the income level at a remote future should bear more uncertainty than the income at a near future."* Rarely will the expectations of the growth rate of the economy, or of consumption, taken at time t about a period $t + 60$ months from now coincide with what is realized 60 months later. Unlike a dice or other static variables, the forecast horizon matters for a dynamic variable such as expected consumption growth that "evolves over time".

In the long run, the forecasting error for a dynamic variable such as consumption growth is large. Therefore, through the way we measure changes in expectations of consumption growth, we manage to capture that uncertainty among investors, something that is missed when expected consumption growth is derived from an autoregressive model (using past realized consumption). As the uncertainty of a forecast increases with the horizon, expected consumption growth should be volatile. A relatively small event might have quite a large implication in the long run.

2.3.5 Consumer Confidence as a Proxy for Expected Consumption

Before we go into details of how we will try to proxy expected consumption growth, we need to define what we mean by it. Expected consumption growth from the agent's point of view is her view about the growth rate of consumption in future periods. It could be seen as an average of consumption growth over a relatively long horizon. We assume that there exists a current belief about what the expected consumption growth rate is, and each innovation in our proxy thus represents a change in belief about expected consumption growth. These innovations is based on changes in the agent's expected ability to consume in the future, which is a function of her expectations about the future growth of the economy and of other factors that affects her "total wealth". Expected consumption growth and actual consumption growth will coincide in some periods, but this is rarely the case when we extend the time horizon as discussed in the previous section.

Innovations in expected consumption growth cannot be directly observed unless we could get into the minds of investors. The proxy would need to be forward looking and capture innovation in agent's beliefs about future economic conditions. The measure needs to be sensitive to new information about the future and would preferably be a spot measure in order to make the measure's relationship to asset data easily testable.

2.3.5.1 Consumer Sentiment and the link to consumption

In this paper we introduce the University of Michigan's Consumer Sentiment Index (CSI) as a reflection of economic growth prospects, and as such, we use it to proxy innovations in expected consumption growth. This allows us to include changes in beliefs about expected consumption growth in a standard factor model framework in a straightforward manner. Consumer confidence is known to predict economic activity, and in the US it is a component of the Index of Leading Economic Indicators. In this section we review the recent literature that discusses the link between consumption growth and CSI.

Carroll, Fuhrer, & Wilcox (1994) conclude that there is a strong contemporaneous correlation between CSI and consumer spending, which to them is not surprising as they note that this correlation simply reflect that when economic conditions are bad, individuals and households cut their spending and at the same time give gloomy responses to interviewers. To them the question was rather whether CSI in itself could predict future changes in consumption. They found that lagged CSI explained about 14 % of growth in personal expenditure on consumption, although the explanatory number decreased to 3% when other forecasting variables, such as interest rates and price changes, were included in the analysis.

Bram & Ludvigson (1998) used the same model but added expenditures on automotive vehicles, services and durable goods. They also compared the two main consumer confidence indices in the US; the University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index and found that they perform very similar in predictive regressions.

Noticeable with the studies that have been made on the link between CSI and private consumption is that they generally test whether growth in CSI_{t-1} predicts growth in $Consumption_t$. It is not that surprising that such a test shows low predictive power in CSI on consumption growth in the coming period, since the CSI measures household's view on business conditions and family income further into the future than only the next month.

More recent studies have confirmed the role of CSI as a predictive variable. Wilcox (2007) acknowledged our comment in the last paragraph, by stating that empirical studies historically have focused on whether consumer sentiment improves 1-quarter-ahead forecasts. He investigated its predictive power on a 4-quarter ahead horizon, and used quarterly data from 1960 to 2006 with personal consumption expenditure as dependant variable and CSI as the independent variable and controlled for disposable income, non-home-equity, home-equity, interest rate and inflation rate. He then regressed both 1-quarter-ahead and 4-quarter-ahead consumption separately on the first four lags of the matrix of dependent variables. The results of the 1-quarter-ahead regression was much in line with previous research and showed only a small incremental improvement in forecasting power from the CSI. However, when added to the rest of the variables, CSI increased adjusted R^2 from 0.31 to 0.35 for private consumption and from 0.39 to 0.45 on durable goods consumption on the 4-quarter-ahead horizon. This is a substantially larger impact than on the shorter horizon.

A recent study by Lahiri, Monokroussos, & Zhao (2012) further adds to the evidence of the predictive power of the CSI. They extend existing models using monthly and real-time data and include a large data set of over 200 explanatory variables at monthly frequency in order to investigate the marginal impact of CSI on consumer spending and thus focus on the change in the model's explanatory power from the addition of the CSI measure. In addition, they test the model on both the CSI and the three indices compiled by the Conference Board. The authors conclude that there is no doubt in the contributions of consumer confidence in explaining consumption expenditures.

It is not surprising that growth in the CSI is not a better predictor of consumption growth in the short-run. As mentioned earlier, innovations in expected consumption growth is a measure of the change in the believed consumption growth rate in the long-term, not in the next period. Therefore, expected consumption growth in this period and actual consumption growth in the next period will seldom coincide. In fact, changes in the CSI could be a perfect proxy for innovations in expected consumption growth on the long horizon, even if it only predicts a part of the realized consumption growth in the short-run. Past research on the link between CSI and consumption confirms that a relationship exists over time, which is all we need for our story to hold.

2.3.5.2 Consumer Confidence and the link to the Stock Market

The relationship between consumer confidence and the stock market has been scrutinized in recent years. For example Otoo (1999) points out that there exists a strong contemporaneous correlation between the return of the stock market and changes in the CSI. He also points out that a rise in the stock market can lead to an increase in future consumer confidence. Otoo notes that there are two possible explanations for this. The first is the *wealth effect*, which is simply that people become wealthier from a rise in the stock market and therefore feel more confident. The second is the *leading indicator effect*, which is that people use the stock market as an indicator for future economic activity and potential income growth.

Fisher & Statman (2003) further verified the strong relationship between CSI growth and stock returns. They find an even stronger relationship between the two due to better timing of the CSI and stocks. They also look at the predictive power of the CSI on stock returns and find that high consumer confidence generally is followed by low returns. Especially on longer horizons (6 months) the CSI explains a significant portion of the returns. The interpretation is the logic we expect, positive growth in the CSI is a sign of increased beliefs about the future economy which raises stock prices, implying lower returns in the future.

As discussed in the previous paragraph there seems to be no doubt that there exists a relationship between the stock market return and growth in the CSI. Even though this relation has been widely acknowledged in academia, it is still debated whether this relationship implies a causal relationship between the two or whether they are driven by a third factor. Many papers have shown that it is the stock market that leads changes in economic conditions and that consumers see the market as an indicator of where the economy is heading. For instance, Jansen & Nahuis (2003) conclude that stock returns granger-cause consumer confidence at very short horizons, but not vice versa and that the relationship is mainly driven by expectations about macroeconomic conditions rather than expectations about personal finances. The causality would according to them, run from the stock market to consumer's confidence.

It is well known that prices on the stock market is a reflection of future economic conditions and it is thus reasonable to assume that uninformed responders of the CSI survey uses the market as an indicator of the future. It is thus not the stock market itself that causes changes in the CSI, but rather what the stock market says about the future. In our point of view the most intuitive explanation of the relation between stock returns and CSI growth is that they are driven by a third factor. When investors' outlook on the future become gloomier (CSI falls), they fear that companies' profits will fall, which is a consequence of deteriorating economic conditions. A fall in expected company profits is reflected in lower stock prices. Hence, the two factors are tightly linked through expectations about future economic conditions.

We believe that the answers by households to the questions forming the CSI are based on almost the same information about the world and the economy as their decisions about investments in the stock market. Having in mind that the investor and consumer is the same agent, it is in our point of view quite obvious that they both are driven by a third factor, being the state of the economy. However, they obviously interpret the information differently as one (the stock market) is a prediction of how well a companies will fare in the future state of the economy and as the other (CSI) is a prediction of how well the individual household will fare in the economy. This is also why the two are not perfectly correlated and why it is interesting to include CSI as a factor and still keep the market factor in the model.

2.4 Expected consumption volatility factor

As mentioned earlier, the separation of the EIS and RRA in the LRR framework allows both innovations in expected consumption growth and innovations in expected consumption volatility to enter the pricing kernel. Many scholars have focused only on volatility as a pricing factor. This section briefly covers the most prominent literature in this field.

2.4.1 Volatility as a risk factor

Several papers, such as Jacobs and Wang (2005), have shown that the risk premia is higher the more negatively an asset's payoff is correlated with consumption variance. A growing part of research within the LRR framework have also investigated consumption volatility risk and found that it has significant implications for asset pricing. Boguth and Kuehn (forthcoming) found that consumption volatility is negatively priced which is consistent with a preference for early solution of uncertainty, a crucial assumption in the LRR framework for an agent with Epstein-Zin preferences. Boguth and Kuehn's consumption volatility factor was significantly robust when included in the Fama-French 3-factor and the Carhart 4-factor model. Tedongap (2010) estimated consumption volatility using a GARCH model and showed that consumption volatility covaries negatively on long horizons for value stocks, hence investors requires a risk premia to hold those assets.

Ang, Hodrick, Zhang, and Xing (2006) found that growth in aggregate volatility proxied by the VIX (Implied Volatility Index) is negatively priced in the cross-section. Since the market risk is a proxy for the investor's wealth and hence consumption stream, these results further strengthens the consistency in theory that consumption volatility or "economic uncertainty" carries a negative price of risk. As mentioned in previous sections, the separation between relative RRA and EIS is necessary for other risks than aggregate consumption to matter. If the estimated price of innovations in expected volatility is significantly negative in our data, it suggests an EIS greater than the inverse of RRA for the representative agent.

In our paper, an increase in volatility of expected consumption growth reflects an increase in economic uncertainty. Intuitively, if times become more uncertain the agent beliefs about the future changes more (is more volatile) than in stable times. If agents value certainty about consumption in the future, then risk related to shocks on expected consumption volatility matters to the investor.

Since we use the CSI as a proxy for investor's expected consumption, we do not need to recover expected consumption growth and volatility through an autoregressive model. Instead we construct different measures of volatility directly from innovations in the CSI data. With this salient feature of the data, we avoid the assumptions and restrictions involved in modelling the dynamics of expected consumption. Given that the CSI is a good proxy for investors' expectations about future consumption it allows us to more directly measure innovations in expected consumption volatility.

Models that assume unobserved states of the economy and model the dynamics of beliefs about expected consumption growth and volatility based on past information (Boguth & Kuehn, forthcoming; Lettau, Ludvigson, & Wachter, 2008), does not account for that expectations about the future state of the economy can, in theory, change independent of the past. Therefore, modelling expected consumption growth can fail to capture large shocks to expectations. Boguth and Kuehn(Forthcoming) estimates high and low states of beliefs about expected consumption growth and volatility based on quarterly data from 1952-2009. Their estimates imply that mean states last for 3.1 years while volatility states last for 7.4 years[3]. They report standard deviations of estimated innovations in expected consumption growth in their paper of 0.19-0.20% for the low volatility state and 0.45-0.48% for the high volatility state. Lettau, Ludvigson and Wachter's (2008) estimates of the standard deviation in growth of expected consumption using the same methodology is 0,56% for the high state and 0,16% for the low state. Using the CSI as proxy, our monthly standard deviation of innovations in expected consumption growth is 5,11% (8,5% for quarterly data), indicating a much higher dispersion in investors' expectations. A data series that proxy for expected consumption growth (given that it is an accurate proxy) will be more volatile than the modelled data, and this is why we believe that our paper is an important contribution to the Long-Run Risks literature.

2.5 The Market factor

In the famous Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965), that builds on the model of portfolio choice developed by Markowitz (1959), it is assumed that investors are

[3] We do not use a switch regime model, and hence cannot compare persistence over time.

risk averse and that they only care about the mean and variance of their portfolio return. Further, it is also assumed that the typical investor's consumption stream is perfectly correlated with the return of the stock market. No other sources of endowment exist in the underlying assumptions of the model. This implies that wealth equals consumption and that consumption should inherit the volatility of the stock market. This is obviously not a realistic view upon the world and therefore it is no surprise that CAPM has not performed well empirically.

Fama & French (2004) note that the early tests of the first version of the CAPM firmly reject the model. Still, the first tests found a positive relation between beta and average return, albeit too flat. The evidence of a too horizontal relation between average return and beta is further confirmed in time-series tests by Black, Jensen and Scholes (1972) and Stambaugh(1982). Since income is a critical determinant of wealth, and income growth and stock market growth are not perfectly correlated, it is not surprising that the CAPM does not hold empirically. Other sources of wealth exist as well in the real world. As a result consumption is not perfectly correlated with the market as the CAPM suggests, especially in countries with a relative small stock market compared to GDP.

However, as long as the representative agent has part of her total wealth invested in the stock market, the market represents an additional real risk for the investor. Assuming an agent with the utility-function suggested by Epstein and Zin, creates a route to include both market return and consumption growth into the marginal utility of wealth (Cochrane J. , 2005a) as long as it is not too correlated with consumption growth. Further, since the market return and CSI is not perfectly correlated for the reasons described in earlier sections (although they are both driven by investor's views about the future growth of the economy) we need to include the market in our model to achieve more reliable estimates of our long-term factors.

3. Empirical Framework

In the following section we shortly present each of our factors and how they are calculated. Each factor is also plotted over time, with the NBER recessions highlighted in the plots, since good factors are business cycle indicators. All variables are based on monthly data over the time period 1979.3-2011.12. The available length of the monthly CSI data limits the length of our empirical tests. We also present summary statistics and a correlation matrix of the factors. This section also includes a presentation of our main test assets, the 25 size and book-to-market portfolios, as well as our additional test portfolios sorted on short-term reversal and size, and long-term reversal and size.

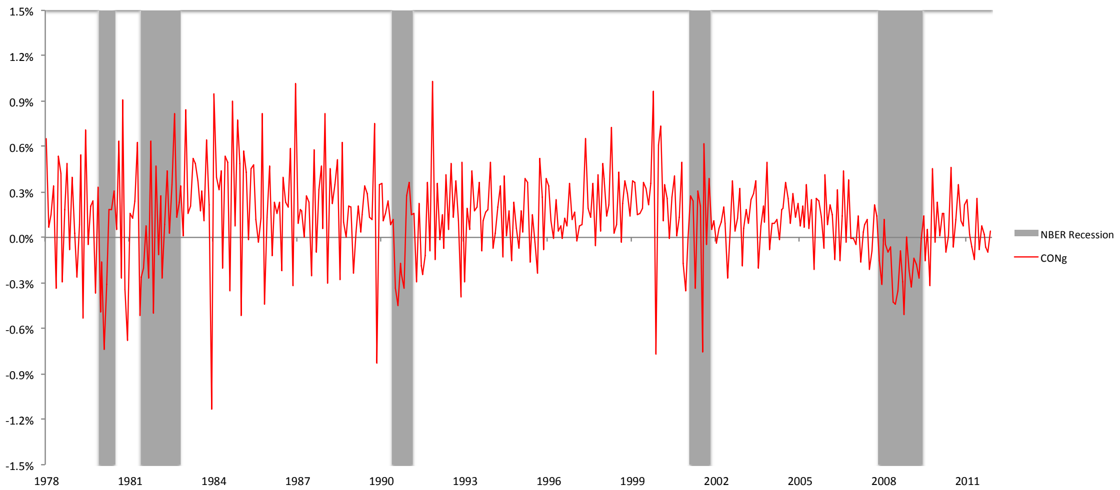
3.1 Consumption factor

The data on consumption in the United States is collected from the database of the Bureau of Economic Analysis, a part of the U.S Department of Commerce[4]. The institute collects data on household consumption across the United States and provide a broad array of different types of personal expenditure. We use monthly observations on personal consumption of nondurables and services as our measure of consumption. By using population data and the consumer price index from the Bureau of Labour Statistics[5], we construct real per capita consumption growth. Consumption of nondurables and services is one of the most widely used proxies for personal consumption expenditure (See for example (Jagannathan & Wang, 2007) and (Lettau & Ludvigson, 2001)).

As discussed by Campbell(2003), the fact that consumption is a flow during a period and closer to an integral rather than a point-in-time observation, creates a timing issue between consumption and spot measures. According to Breeden, Gibbons, & Litzenberger (1989) this creates a "summation bias" and a timing convention is needed to better match the factors. Campbell discusses the "beginning-of-period" timing convention versus the "end-of-period" timing convention. We choose to see consumption as measured in the beginning of the period. Then consumption growth is next period's consumption by this period's consumption.

$$\boldsymbol{CONg_t} = \ln \frac{(CON_{t+1})}{(CON_t)}$$

Figure 1.



Looking at consumption growth plotted over time it seems like it is fluctuating slightly more in times of recession. Notably though is that the volatility in consumption growth seems to have decreased over time. The lowered decrease in macroeconomic volatility during the last 15 years

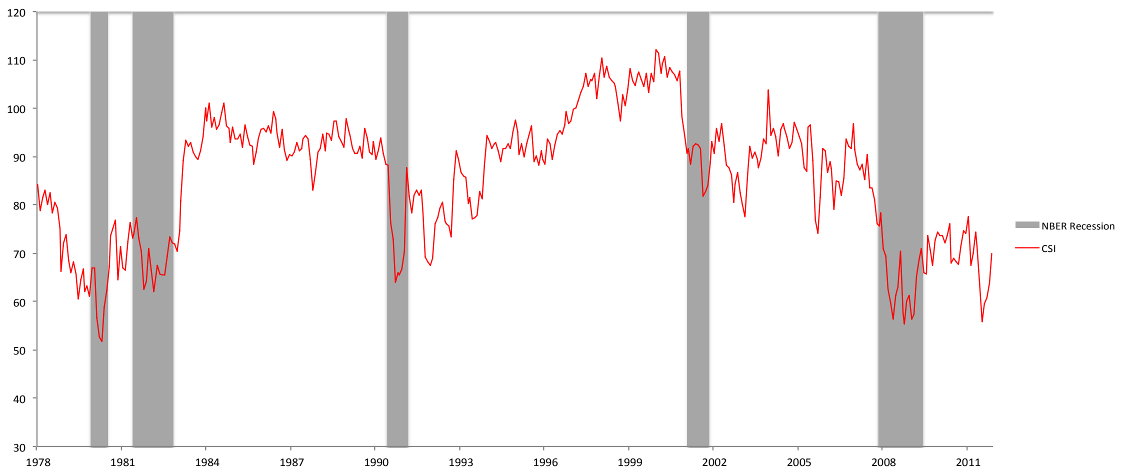
4 (http://www.bea.gov/national/consumer_spending.htm)
5 (http://www.bls.gov)

of the 20th century across sectors, among them being consumption, has been discussed widely in academia (Watson & Stock, 2002; Blanchard & Simon, 2001; Lettau, Ludvigson, & Wachter, 2008).

3.2 Expected consumption factor

We use the University of Michigan's consumer sentiment index (CSI) as proxy for innovations in the representative agent's expected consumption growth. Another major index is the Conference Board's Consumer Confidence Index. Although the questions in the different surveys are slightly different, they are highly correlated. Since the survey conducted by the University of Michigan is the most widely used by both practitioners and researchers, we only use this index to for our empirical tests. The evolution of the CSI *raw data* over time is plotted below in figure 2. The grey areas represent NBER Recessions.

Figure 2.



The Michigan survey of consumer sentiment has been conducted monthly since 1978. The CSI is based on answers to five questions that are part of a broader survey (see appendix I for the questions). The entire Michigan survey is made up of around 50 core questions that are designed to capture consumer attitudes and expectations. It is based on at least 500 telephone interviews that are conducted during each month. The raw data on the Michigan Consumer Sentiment Index is collected from the database of the Federal Reserve Bank of St Louis[6].

The index was created with the following objectives according to the University of Michigan:

- To assess near-time consumer attitudes on the business climate, personal finance, and spending.
- To promote an understanding of, and to forecast, changes in the national economy.
- To provide a means of incorporating empirical measures of consumer expectations into models of spending and saving behaviour.

6 (http://research.stlouisfed.org/fred2/series/UMCSENT/)

- To gauge the economic expectations and probable future spending behaviour of the consumer.
- To judge the consumer's level of optimism/pessimism.

The survey is conducted over an entire month (Bram & Ludvigson, 1998). This implies that on average it represents consumer sentiment in the middle of the month. Therefore, a similar problem with timing occurs as for consumption data. In order to be consistent, we use the beginning of the period timing convention for CSI_t as well when we calculate the factor.

$$\boldsymbol{CSIg_t} = \ln \frac{(CSI_{t+1})}{(CSI_t)}$$

Figure 3.

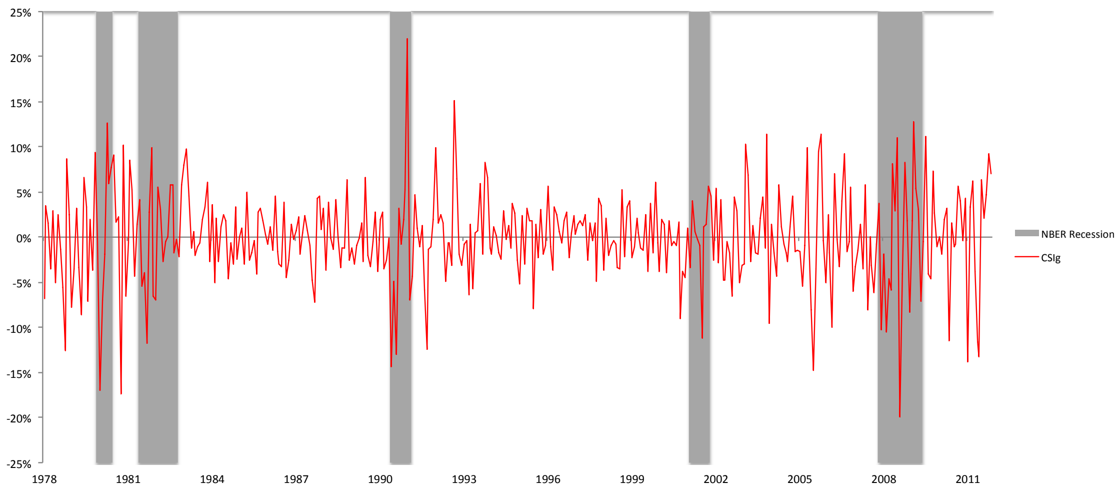


Figure 3 plots log growth of the CSI Index (the *expected consumption factor*). As discussed in the literature section of this paper, there is as expected a notable increase in the volatility of CSI_g (innovations in expected consumption growth) in times of recession, which implies that it is a sensitive indicator of the business cycle. This is highly important for validating CSI as a good proxy for innovations in expected consumption growth.

3.3 Expected consumption volatility factor

Different measures of consumption volatility have been used successfully in past research. Tedongap(2010) uses a GARCH specification to capture volatility and finds a negative covariance between value stocks and innovations in beliefs about consumption volatility. Bansal, Khatachtrian and Yaron(2005) use both an AR(1)-GARCH(1,1) specification and a non-parametric measure of volatility. The latter inspired by the work of Andersen, Bollerslev, and Diebold (2005), where volatility is defined as the innovations in the sum of squared residuals from an AR(1) on consumption growth over different lags of quarterly data. Bansal et al.(2005) found that both the measurements of innovations in volatility provide similar results. In our paper, we use two non-parametrical measures of volatility and one parametric measure.

We reflect "economic uncertainty" in the agent's assessment of expected consumption growth. Intuitively, the more uncertain the times, the more uncertain the agent is about the future consumption growth (the higher the volatility in the agents assessment of expected consumption growth).

The first measure of volatility is similar to the non-parametric measure used by Bansal, Khatachtrian, and Yaron (2005), where we measure the innovation in the volatility of expected consumption growth by taking the sum of absolute residuals[7] from an AR(1) on the CSI.

$$g_{CSI,t} = g_{CSI,t-1} + n_{CSI,t}$$

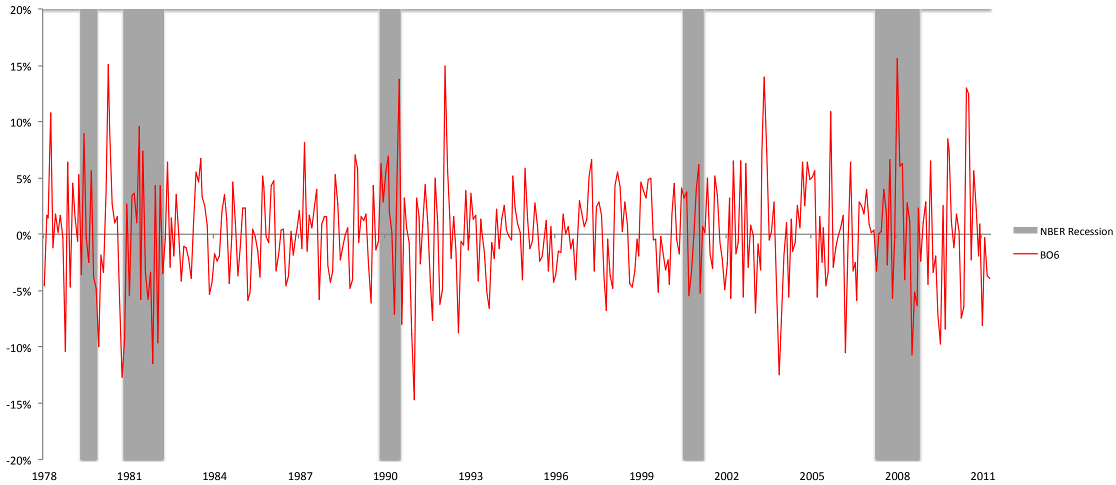
$g_{CSI,t}$ is CSI growth, and $n_{CSI,t}$ the residuals from an AR(1).

$$BO_{t-1,j} = \sigma_{CSI,t-1,j} = \sum_{t=1}^{J} |n_{CSI,t-j}|$$

Where $\sigma_{CSI,t-1,j}$ is the sum of absolute residuals, which characterize the level of uncertainty in expected consumption growth. J denotes the amount of lags used to calculate the sum. Instead of weighting the importance of each lag, we follow the recommendation by Andersen, Bollerslev, & Diebold (2005) and use the sum of the residuals on relatively short lags in our empirical tests, j=3 and 6. The factor is then created as the innovation (growth) in the BO volatility series thus capturing the innovation in the volatility of expected consumption growth:

$$\boldsymbol{BOg_{t,j}} = \frac{(1 + BO_{t,j})}{(1 + BO_{t-1,j})} - 1$$

Figure 4.



The plot of BO6, (growth in expected consumption volatility using 6 lags), over time, also shows a tendency of capturing increased activity during recessions. All recessions except the

7 We use absolute residuals instead of squared residuals to make the measure less sensitive to outliers, as discussed by Bansal, Khatachtrian and Yaron(2005)

one during the dot-com crisis around the beginning of the century coincide with an increase in innovations of volatility in BO6.

Our second volatility measure is also a non-parametric measure of volatility and is simply the sum of absolute log growth of the CSI index over *j*=3 and 6 lags.

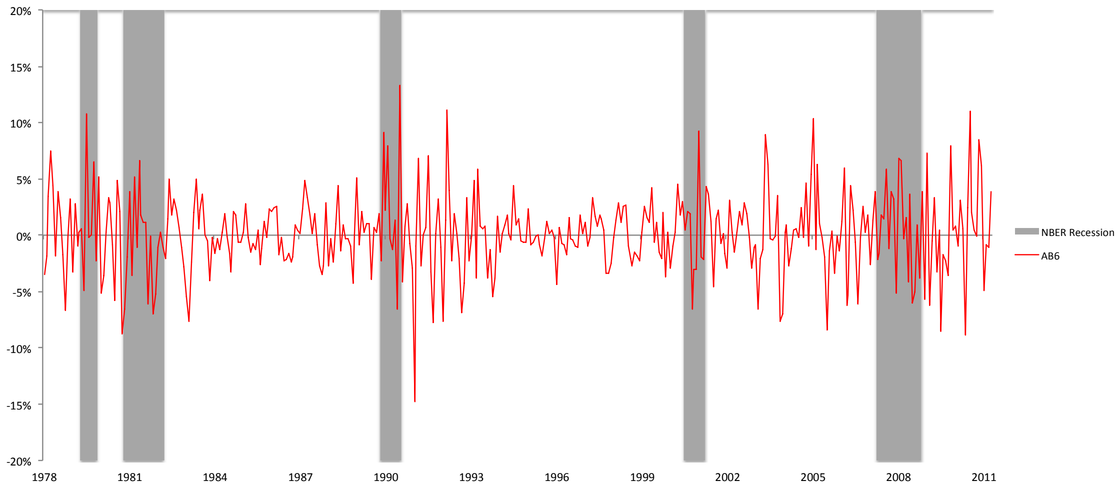
$$AB_{t-1,j} = \sigma_{CSIg,t-1,j} = \sum_{t=1}^{J} \left| CSI_{g,t-j} \right|$$

where *j* denotes the number of lags we have used to model volatility.

The factor is created as the innovation in the AB volatility series:

$$\boldsymbol{ABg_{t,j}} = \frac{(1 + AB_{t,j})}{(1 + AB_{t-1,j})} - 1$$

Figure 5.



Above the growth series AB6 is plotted over time and we see wide fluctuations in volatility. In the booming 80s and the end of the 90s volatility is low. As expected, we see indications of an increase in the innovations of volatility in times of economic crisis, except during the recent financial crisis.

Our third measure of volatility is based on modelling expected consumption growth as following an GARCH(1,1) process. This implies that we model volatility as:

$$GAR = \sigma_{t,CSIg} = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2$$

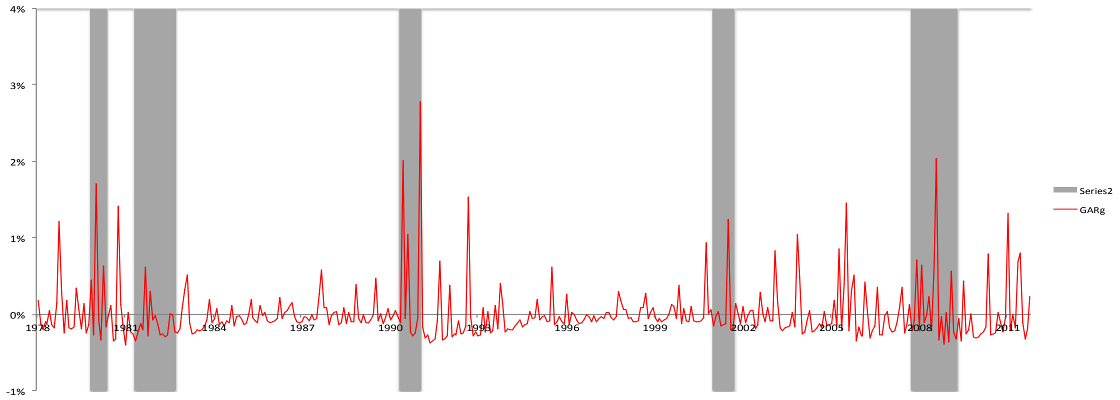
where

$$u = \frac{CSIg_t - CSIg_{t-1}}{CSIg_{t-1}}$$

and β the weight last period's volatility gets on this period's volatility. The factor is created as the innovation in the GAR volatility series:

$$\boldsymbol{GARg_t} = \frac{(1 + GAR_t)}{(1 + GAR_{t-1})} - 1$$

Figure 6.



The plot of $GARg_t$ shows distinct peaks in recession times implying that the factor is a good business cycle indicator.

To simplify, from now on we supress the *g* in all our volatility notations. For example GAR represents $GARg_t$. $BO6$ represents $BOg_{t,j=6}$ where 6 lags have been used to calculate the sum of absolute residuals in the first step.

3.4 Market factor

The data on the market risk premium was collected from Kennet R. French's website. He uses the value-weighted return of all CRSP firms incorporated in the US and listed on the NASDAQ, NYSE or AMEX, that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of time *t*, and good return data for *t* to calculate the market factor.

The market factor is simply calculated as:

$$\boldsymbol{MKT} = R^e = R^m - R^f$$

where R^m is the market return and R^f is the risk-free rate.

3.5 Summary statistics of factors

Table 1.

Summary Statistics of Factor growth

The sample period is 1979.03-2011.12. The number next to the AB and BO series denotes the number of lags used in the calculations.

	Mean	SD	Skewness	Excess Kurtosis	Min	Max
MKT	0.59%	4.60%	-0.72%	2.16%	-23.00%	12.50%
CONg	0.13%	0.30%	-0.18%	1.25%	-1.14%	1.03%
CSIg	0.02%	5.11%	-0.17%	1.93%	-19.92%	21.97%
AB3	0.08%	5.27%	0.20%	1.07%	-17.90%	21.36%
AB6	0.07%	4.59%	0.16%	0.92%	-14.72%	15.57%
BO3	0.08%	3.97%	0.37%	2.40%	-13.69%	19.65%
BO6	0.07%	3.52%	0.14%	1.70%	-14.82%	13.28%
GAR	0.00%	0.36%	3.45%	16.49%	-0.40%	2.78%

3.6 Correlation matrix of factors

Table 2.

Correlation matrix of factor growth

1979.03-2011.12.

	MKT	CON_G	CSI_G	AB3	AB6	BO3	BO6	GAR
MKT	100.00							
CON_G	24.17	100.00						
CSI_G	19.20	8.24	100.00					
AB3	-6.50	-5.08	1.31	100.00				
AB6	-4.45	-5.99	0.44	51.88	100.00			
BO3	-7.29	-8.55	0.25	53.00	27.01	100.00		
BO6	-8.63	-7.50	0.35	26.83	51.98	51.78	100.00	
GAR	-14.23	-4.76	-9.67	11.26	1.91	39.08	35.83	100.00

The correlation matrix above confirms that the risk for multi-collinearity is low for the model specifications that we run (we only include one volatility factor at a time). In the table above it is noticeable that CON_g is only correlated to the MKT at 24.2%, which is far from the 100% correlation assumed by the CAPM. This low level of correlation ensures that we can include both *CONg* and MKT in the same factor model.

3.7 Stationarity tests

When working with time series data it is of high importance to investigate whether the time series are stationary or not. A stationary time series is one where the distribution of innovations is constant through time. If a time series is not stationary a possible transformation is needed to induce stationarity.

To test for stationarity we perform a simple unit root test using an autoregressive model. The most well-known test is the augmented Dickey-Fuller test, where the hypothesis $\gamma = 0$ model is tested in the following model:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-j+1} + \epsilon_t$$

where α is a constant, β the coefficient of a time trend and j the lag order of the autoregressive process.

Table 3.

Augmented dickey fuller test of stationarity of factor growth

The montly factor growth series are 1979.03-2011.12.The test is performed based on 24 lags

Factor	Test Statistic	P-value
MKT	-18.19	0
CONg	-7.37	0
CSIg	-4.39	0
AB3	-6.43	0
AB6	-6.97	0
BO3	-7.11	0
BO6	-6.61	0
GAR	-20.31	0

In all tests the null hypothesis of a unit root is rejected at 99% significance level.

3.8 Test assets

3.8.1 Size and book-to-market portfolios

As our main test assets, we use the 25 Fama-French size and book-to-market portfolios from Kennet R. French's website. These portfolios have high dispersion in returns over time and have been commonly used in related empirical studies. The portfolios are intersections of five portfolios sorted on size (Market cap) and five portfolios sorted on value (book-to-market). We construct real excess returns by subtracting the 1-month t-bill and deflate by the consumer price index (CPI) downloaded from the Bureau of Labor Statistics. The length of the test period is limited by the availability of the length of the monthly CSI data. The effective start date of our empirical tests is 1979.03. The summary statistics of the size and book-to-market portfolios can be found in appendix III.

3.8.2 Additional test assets for robustness

In addition to testing our model on the 25 size and book-to-market portfolios we also include two other set of test assets. These are the 25 short-term reversal and size portfolios, and the 25 long-term reversal and size portfolios collected from Kennet French's website. Both are sorted on size, but the short-term reversal portfolios are also sorted on prior (1-1) monthly return, whereas the long-term reversal portfolios are sorted on prior (13-60) monthly return. The summary statistics of the two sets of assets can be found in appendix III.

4. Methodology and test results

In this chapter we begin by presenting some basics about factor pricing models and a decomposition of the asset pricing implications of our model. This is followed by a thorough review of the cross sectional asset pricing methodology we have employed to retrieve the empirical results we present at the end of this section.

4.1 Basics of factor pricing models

In theory the CCAPM should explain the full cross section of asset returns by pricing the factors according to their exposure to consumption growth. However, in practise the model does not work well. This has opened up to tie the discount factor m to other factors and create a factor pricing models to represent the stochastic discount factor in the following way:

$$m_{t+1} = a + b' \ f_{t+1}$$

A factor-pricing model aims to find variables that are a proxy for aggregate marginal utility growth, which we can test in the format of:

$$E(R_{t+1}) = a + \beta^{'} \lambda$$

The cross sectional asset pricing study in this paper is cantered around testing the following hypothesis:

$$H^0: \quad E(R_t) = \gamma_0 1_N + \gamma_1 \beta_1 + \cdots + \gamma_K \beta_K$$

where $E(R_t)$ is a vector of expected return on the N test assets, $\beta_1,\ldots, \beta_K$ are N-vectors of risk exposures to K factors, and $\gamma = (\gamma_1, \ldots, \gamma_K)^{'}$ is a vector of K risk premia.

The common data-generating process is a multi-factor regression model:

$$r_{i,t} = a_i + \beta_{i,1} f_{1,t} + \cdots + \beta_{i,K} f_{K,t} + \epsilon_{i,t}$$

where,

$r_{i,t}$ = excess return on asset i in period t

$f_{k,t}$ = realisation of the innovation in the k-th factor in period t

$\epsilon_{i,t}$ = random errors

T = number of time-series observation

4.2 Asset pricing implications of our model

At this stage we believe it is of value to the reader to summarize and more clearly define our factors and their link to the LRR framework. As stated before our main purpose of the paper is to explain the real risks that the investor faces. We propose the following model for explaining the expected return of an asset:

$$E\left(R^e_{i,t+1}\right) = Cov_t\left(R^e_{i,t+1}, \Delta MKT_{t+1}\right) + Cov_t\left(R^e_{i,t+1}, \Delta C_{t+1}\right) + Cov_t\left(R^e_{i,t+1}, \Delta E(C_{t+1})\right) + Cov_t\left(R^e_{i,t+1}, \Delta\sigma E(C_{t+1})\right)$$

The expected return of an asset is thus determined by its *covariance with*: consumption growth, innovations in expected consumption growth, innovations in the volatility of expected consumption growth respectively and the market return (our full model specification). The main variables of interest in our tests are innovations in expected consumption growth and volatility.

If we assume that the EIS is larger than the inverse of the relative risk aversion, the asset pricing implication of the factors in focus of this study are (1) Investors require a risk premia to hold assets with a positive covariance with innovations in expected consumption growth, since these assets payoff poorly when the agents beliefs about the future consumption growth falls: The price of risk is positive. (2) Investors require a risk premia to hold assets with a negative covariance with innovations in expected consumption volatility, since these assets payoff poorly when uncertainty increases: The price of risk is negative.

Our analysis is mainly focused around how our expected consumption growth factor (CSI_g) and our factors measuring the growth in expected consumption volatility (GAR, AB and BO) perform in the cross section. The performance of MKT and CON_g will also be commented but is not the main focus of this paper.

4.3 Cross-sectional asset pricing methodology

In the case where the model factors are returns there are two different ways of testing the asset pricing model; using a time-series approach or using a cross sectional approach. However, when the factors are not returns, as is the case of our model, a linear time-series regression will not be enough to estimate factor premias. The alternative is then to either use *a two-step cross sectional approach* (Cochrane, 2005b) or to follow the *Fama-Macbeth procedure* (Fama & MacBeth, 1973). The main difference between the two methods lies in the calculation of standard errors of the estimates. An advantage with the Fama-Macbeth(FM) procedure is that it allows for the beta to change over time. If the betas remain the same over time, the two approaches yield the same estimates.

As noted by Cochrane (2005b), in a regular regression of the form $Y_i = X_i b + \varepsilon_i$ the error terms are not correlated with each other. In our multivariate regression the error terms α are most probably correlated with each other. If one portfolio has a low α, the next one is also likely to have a low α. Therefore we need standard errors that correct for correlation across assets. The FM procedure is the simplest method for addressing the inference problems caused by correlation between residuals in cross-sectional regressions. Cross-sectional correlation when using panel data was for long a serious issue but this methodology provided a simple solution. The two-step cross sectional approach does not automatically adjust for this but it is possible through a somewhat complicated standard error calculation as shown in appendix IV.

The advantage of the two-step cross sectional approach is that it allows us to use more robust standard errors by correcting for the fact that the betas are estimated in the first-pass, a problematic first proposed by Shanken (1992). Such a correction is possible in the FM procedure, but according to Boguth & Kuehn (forthcoming) it would require keeping track of standard errors across all stages of estimation and is thus not feasible in practise. Following the work of Boguth & Kueh(2012) , Hodrick, Zhang & Xing(2006), and (Tedongap & Farago, 2012) we use the FM procedure (thus disregarding the estimation bias).

4.4 Fama-Macbeth procedure

4.4.1 Step 1. Time-series regression to retrieve betas

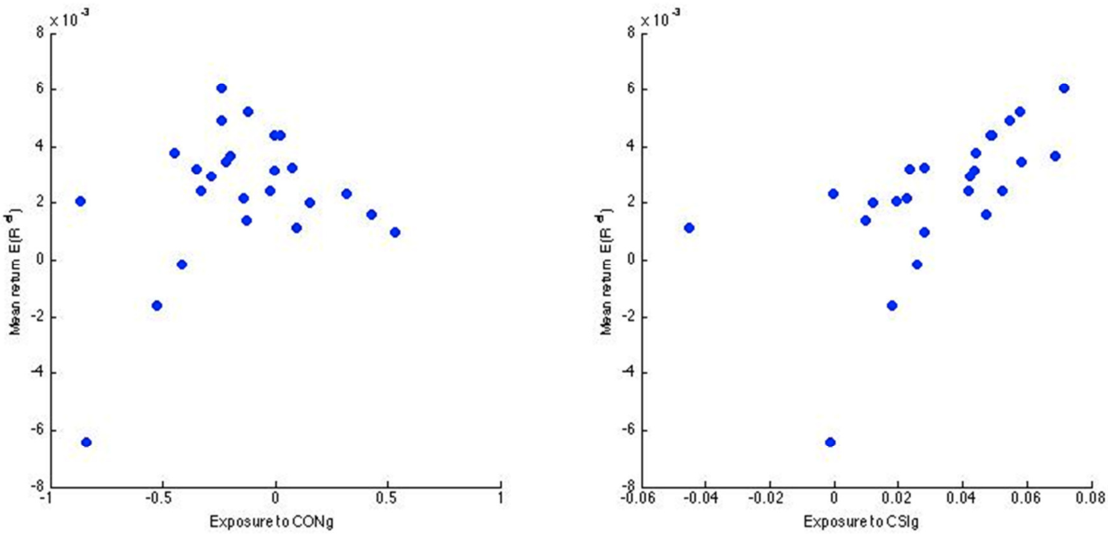
We first estimate the risk loadings (betas) of the factors in a time-series regression using the 25 portfolios as test assets:

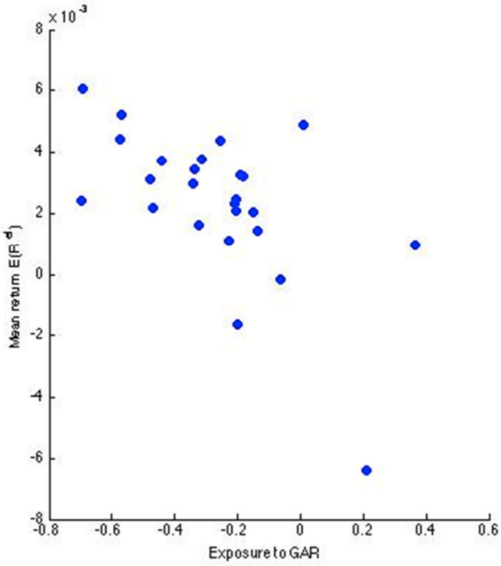
$$R_{i,t}^{e} = a_i + \beta_{i,1} f_{1,t} + \cdots + \beta_{i,K} f_{K,t} + \varepsilon_t^i,$$
$$t = 1,2,\ldots,T \quad \text{for each i,} \quad i = 1,2,\ldots,N \;\;, k = 1,2,\ldots,K$$

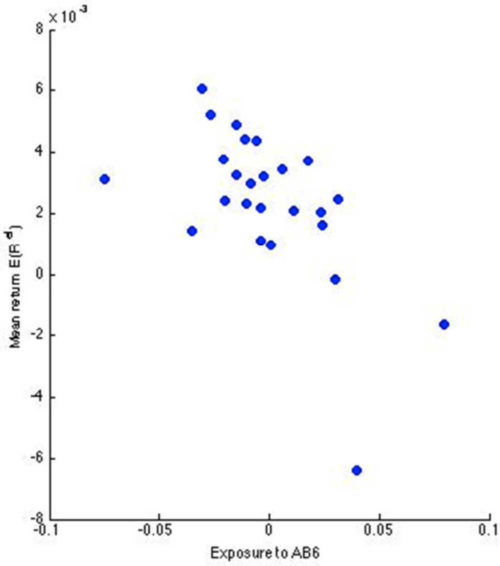
We then collect the betas from this regression and use them in the subsequent cross-sectional regressions (second-pass).

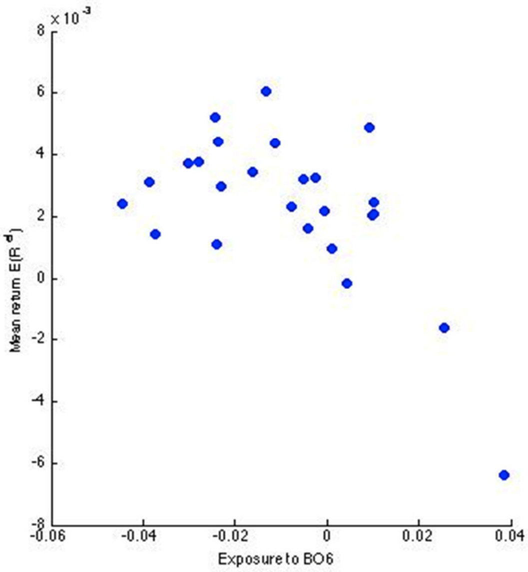
By plotting the betas (risk loadings) one by one from a first-step 4-factor regression against the mean return of the portfolios (figure 7), we get an initial picture of how well each factor manage to explain the excess returns of the portfolios. The respective betas used for the graphs are estimated in the following 4-factor regressions: betas for CON_g, CSI_g, and GAR are estimated in a regression including MKT, CON_g, CSI_g and GAR. The betas for $AB6$ and $BO6$ have each been estimated by replacing GAR in the otherwise same 4-factor model.

Figure 7. Beta vs. Mean return of portfolios









By observing the graphs we can see that the pattern discussed in the literature section of this paper exists across all our factors. Most notably is the strong pattern for CSI_g, where the positive relation suggests that a high exposure to the factor is associated with a high excess returns. For CON_g the relationship is vaguer even though the relationship is positive as suggested by theory. We chose to plot three of our volatility factors; $BO6$ and $AB6$ (6 lags) and GAR. The negative relationship is obvious in all three plots; a high exposure to innovations in economic uncertainty is associated with lower expected returns. This is in line with what theory predicts, as investors like assets that pay off positively when times become more uncertain and are willing to pay more to hold these assets.

4.4.2 Step 2. Cross-Sectional Regression to retrieve Lambda (Price of risk)

Using the betas estimated in the time-series regression, we run a second regression across assets at every time t of the form:

$$R_{i,t}^{e} = \hat{\beta}_{i,f^1}\lambda_{1,t} + \cdots + \hat{\beta}_{i,f^K}\lambda_{K,t} + \alpha_{i,t}$$

In the above regression, the βs are the explanatory variables, λ the regression coefficients and the residuals α_i represent the pricing errors of the cross sectional regression.

The factor risk premium λ and pricing error α is then estimated as the average across time:

$$\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_t \qquad \hat{\alpha}_i = \frac{1}{T}\sum_{t=1}^{T} \hat{\alpha}_{i,t}$$

Standard errors of λ and α in a Fama-Macbeth regression are estimated as:

$$\sigma^2(\hat{\lambda}) = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\lambda}_t - \hat{\lambda})^2, \qquad \sigma^2(\hat{\alpha}_i) = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\alpha}_{i,t} - \hat{\alpha}_i)^2$$

Some of our volatility factors (AB and BO) are based on an overlapping time series, thus we might find that the errors from the regressions are serially correlated. This would potentially create a bias in the standard errors, so a correction is needed. To account for this we calculate Newey West(1987) standard errors with lags equal to the *j* number of lags we use to estimate the volatility measurement. For example, when we include *AB3* as volatility factor, we use the Newey West standard errors with three lags for all our estimates. The t-statistic of the lambda standard errors are calculated as[8]:

$$\frac{\lambda^k}{cov(\lambda)_{k,k}} \sim t_{N-K}$$

in the regressions without an intercept and as:

$$\frac{\lambda^k}{cov(\lambda)_{k,k}} \sim t_{N-K-1}$$

in the regressions with a free intercept.

Due to computational limitations in the FM procedure we run a separate two-pass approach to calculate the χ^2 statistics to account for estimation bias in the first step and cross-correlation following the methodology presented by (Cochrane, 2005b) (See appendix for a detailed explanation of this methodology.) The χ^2 statistic are calculated to test whether the pricing errors from our model are jointly different from zero or not.

The pricing errors of the regressions without an intercept are tested as:

$$\hat{\alpha}' \; cov(\hat{\alpha})^{-1}\hat{\alpha} \sim \chi^2_{N-k}$$

and in the regressions with an intercept they are tested as:

$$\hat{\alpha}' \; cov(\hat{\alpha})^{-1}\hat{\alpha} \sim \chi^2_{N-k-1}$$

Cochrane mentions three ways of calculating cross sectional R^2. In the regressions with a free constant it is calculated as:

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{var(alpha)}{var(expected\ returns)}$$

In the case of no intercept we force the regression to run through the origo, so we chose to calculate the R^2 slightly different. There seems to be no consensus on which methodology is

[8] The lower index k, k denotes the k'th element on the diagonal of $cov(\lambda)$

correct when calculating R^2 in a regression without a constant. Different specifications provide different estimations of R^2. We chose the following specification, as the estimates calculated differently otherwise are largely negative under many circumstances.

$$R_0^2 = \frac{SSR}{SST} = \frac{var(predicted\ returns)}{var(expected\ returns)}$$

However, this will often provide quite inflated estimations of R^2. We have that in mind and mainly use R^2 for comparative reasons of the explanatory power of different model specifications. Therefore, the drawbacks are not too material for us.

4.5 Regression output

Table 4.

Fama-Macbeth No Constant

The sample period is 1979.03-2011.12. The test assets are downloaded from Kenneth French's website and are the 25 portfolios sorted on size and book-to-market. The number next to the AB and BO series denotes the J-th lags in the calculations. In the upper part, each factor is tested alone in the cross section. The second part show results of our model without the market factor(MKT). The third section comprises results from different specifications of our 4-factor model. The lower part includes estimates of the FF-3 and Carhart 4-factor model. All estimates and the Root Mean Square Errors(RMSE) are multiplied from monthly to annual estimates and reported in %. All t-statistics are corrected for heteroskedasticity and autocorrelation using Newey-West standard errors with j-lags. Numbers in bold are statistically significant at the 90%-level. Due to technical reasons, the X^2-statistics are calculated in a two-pass regression adjusted for estimation bias in the first-stage and correlated errors following Shanken(1992). X^2 in bold show statistics where the pricing errors are not jointly significantly different from zero.

MKT	CONg	CSIg	GAR	AB3	AB6	BO3	BO6	HML	SMB	MOM	R^2	AdjR^2	RMSE	X^2
0.24											0.02	-0.02	3.26	127
(0.98)														
	0.09										0.02	-0.03	3.14	105
	(1.02)													
		1.04									0.03	-0.02	3.07	117
		(1.04)												
			-0.12								0.03	-0.01	3.03	110
			(-0.97)											
				-3.01							0.04	0.00	2.95	80
				(-1.02)										
					-4.62						0.19	0.15	2.61	44
					(-1.20)									
						-3.25					0.06	0.02	2.94	92
						(-1.02)								
							-2.78				0.03	-0.01	2.89	93
							(-1.06)							
	-0.09	0.30	-0.22								0.09	-0.04	2.99	77
	(-0.82)	(0.19)	(-1.69)											
	-0.14	1.04		-4.91							0.15	0.02	2.88	41
	(-1.30)	(0.59)		(-1.67)										
	-0.12	1.55			-5.43						0.31	0.21	2.54	**30**
	(-1.07)	(1.01)			**(-2.57)**									
	-0.04	0.08				-5.50					0.15	0.02	2.91	54
	(-0.37)	(0.03)				**(-1.84)**								
	-0.16	0.69					-6.49				0.20	0.09	2.74	**34**
	(-1.31)	(0.42)					**(-1.88)**							
0.08	0.27	6.52									0.54	0.48	2.25	**30**
0.35	**(1.73)**	**(3.98)**												
0.03	0.27	4.40	-0.40								0.64	0.56	2.03	**28**
(0.13)	**(1.71)**	**(3.31)**	**(-2.39)**											
0.08	0.23	6.02		-1.63							0.54	0.45	2.23	**33**
(0.31)	**(2.10)**	**(3.34)**		(-0.73)										
0.12	0.17	5.58			-4.01						0.64	0.57	1.92	**26**
(0.46)	(1.32)	**(3.07)**			**(-2.22)**									
0.08	0.26	5.49				-2.85					0.58	0.50	2.09	**33**
(0.31)	**(1.82)**	**(2.56)**				(-1.13)								
0.08	0.17	5.28					-4.79				0.60	0.52	2.04	**30**
(0.31)	(1.46)	**(3.11)**					(-1.57)							
								0.18	0.53	-2.45	0.59	0.53	2.24	93
								(0.85)	**(2.30)**	(-1.65)				
(0.12)								(0.09)	(0.64)		0.42	0.34	2.38	122
(0.53)								(0.56)	**(2.80)**					
0.08								0.13	0.53	-2.03	0.51	0.41	2.16	101
(0.33)								(0.87)	**(2.33)**	**(-2.61)**				

Table 5.

Fama-Macbeth free constant

The sample period is 1979.03-2011.12. The test assets are downloaded from Kenneth French's website and are the 25 portfolios sorted on size and book-to-market. The number next to the AB and BO series denotes the J-th lags in the calculations. In the upper part, each factor is tested alone in the cross section. The second part show results of our model without the market factor(MKT). The third section comprises results from different specifications of our 4-factor model. The lower part includes estimates of the FF-3 and Carhart 4-factor model. All estimates and the Root Mean Square Errors(RMSE) are multiplied from monthly to annual estimates and reported in %. All t-statistics are corrected for heteroskedasticity and autocorrelation using Newey-West standard errors with j-lags. Numbers in bold are statistically significant at the 90%-level. Due to technical reasons, the X^2-statistics are calculated in a two-pass regression adjusted for estimation bias in the first-stage and correlated errors following Shanken(1992). X^2 in bold show statistics where the pricing errors are not jointly significantly different from zero.

MKT	CONg	CSIg	GAR	AB3	AB6	BO3	BO6	HML	SMB	MOM	R^2	AdjR2	RMSE	X^2
-1.04											0.41	0.38	2.26	73
(-1.86)														
	-0.30										0.20	0.16	2.64	49
	(-1.92)													
		-1.22									0.03	-0.01	2.89	92
		(-0.67)												
			0.07								0.01	-0.03	2.93	92
			(0.45)											
				-1.38							0.01	-0.03	2.93	87
				(-1.07)										
					-4.97						0.22	0.18	2.61	89
					(-2.47)									
						-1.66					0.02	-0.03	2.92	89
						(-0.97)								
							-3.06				0.04	-0.01	2.89	67
							(-1.55)							
	-0.33	-0.77	-0.10								0.22	0.10	2.61	41
	(-2.33)	(-0.42)	(-0.97)											
	-0.33	-0.09		-2.39							0.23	0.11	2.59	38
	(-2.10)	(-0.05)		(-1.10)										
	-0.25	0.68			-3.84						0.31	0.21	2.44	33
	(-1.64)	(0.41)			**(-2.89)**									
	-0.29	-1.11				-4.09					0.26	0.15	2.54	38
	(-1.90)	(-0.47)				(-1.56)								
	-0.31	-0.08					-3.41				0.24	0.13	2.56	37
	(-1.90)	(-0.05)					(-1.42)							
-0.90	4.75	0.01									0.66	0.61	1.71	**31**
(-1.79)	**3.34**	(0.11)												
-0.85	0.03	3.26	-0.29								0.72	0.67	1.54	**20**
(-1.67)	(0.27)	**(2.47)**	**(-2.24)**											
-0.98	0.03	5.14		1.61							0.67	0.61	1.68	**26**
(-1.93)	(0.31)	**(3.06)**		(1.10)										
-0.70	0.02	4.71			-1.67						0.68	0.61	1.67	**29**
(-1.30)	(0.19)	**(2.94)**			(-1.51)									
-0.88	0.01	4.30				-1.45					0.67	0.60	1.70	33
(-1.67)	(0.12)	**(2.15)**				(-0.63)								
-0.83	0.01	4.63					-1.11				0.66	0.60	1.70	**31**
(-1.75)	(0.08)	**(2.91)**					(-0.57)							
								0.08	0.50	-1.70	0.46	0.39	2.15	81
								(0.55)	**(2.16)**	**(-2.17)**				
-1.49								0.00	0.28		0.58	0.52	1.91	63
(-4.11)								(0.01)	(1.22)					
-1.72								0.05	0.09	-2.43	0.71	0.66	1.57	45
(-4.80)								(0.32)	(0.43)	**(-3.13)**				

The results from the FM procedure are summarized above in table 4 for regressions without constant, and in table 5 for results including a free constant. For each estimate we report the estimate of the risk premiums (the coefficients) and t-statistics. All t-statistics are corrected for heteroskedasticity and autocorrelation using Newey-West(1987) standard errors with j-lags. We also present R^2, adjusted R^2, root mean squared errors (RMSE) and χ^2 statistics. The coefficients and RMSE are multiplied by 12 and presented as annual numbers. The third section comprises estimates of our 4-factor model; MKT, CON_g, CSI_g are included in all specifications in this section, and in each row we include one volatility factor.

In the 4-factor model, innovations in expected consumption growth (CSI_g) is priced in all regressions. Contrary to the findings of Boguth and Kuehn (forthcoming), who found innovations in expected consumption growth insignificant, our findings suggests that it is priced and that the economic significance is large with a risk premium ranging between 4,4-6,35% on an annual basis for the regressions without a constant and between 3.26-5.14% in the tests with a free constant. The pricing implication of expected consumption growth is thus as expected; investors require a risk premia to hold assets with payoffs that covaries positively with innovations in expected consumption growth.

In our model, growth in expected consumption volatility is priced for GAR and $AB6$ in the model without a constant and for GAR in the model with a free constant. As predicted by the theory in the Long-Run Risks literature, the price of risk is negative for all volatility specifications. Investors dislike uncertainty and therefore prefer an asset that pays off in uncertain times. These assets covary positively with innovations in expected consumption volatility and therefore are valuable for the investor and will thus carry a lower expected return (compared to assets with a poor payoff when uncertainty increases.) These finding is expected for an agent with an EIS larger than the inverse of RRA and who prefers early resolution of uncertainty. Regarding economic significance, GAR is rather small at -0.4%(table 4) to -0.29% (table 5) on an annual basis, while it is larger at -4.01% for $AB6$ (table 4). The significant negative price of risk for consumption volatility in our findings is consistent with prior research in the LRR literature (Ang, Hodrick, Zhang, & Xing, 2006; Boguth & Kuehn, forthcoming; Tédongap, 2010).

Short-term consumption risk CON_g is significant in almost all of our 4-factor regressions without a constant and insignificant in all of our tests with a free constant. The sign of the risk premium is positive as predicted by theory, although the economic significance is generally small at around 0.25% annually.

Noticeable is that the market adds a lot to the R^2 in the regressions both with and without a constant, but as mentioned earlier in the paper, we need to be careful with drawing too much inference from the R^2 statistics in the no constant regressions. The significance of the market factor is driven out by the other factors in our 4-factor model in the regressions without a constant. The weak insignificant results for the market factor in the pricing of these 25 portfolios sorted on value and size has been widely discussed in academia. One explanation could bet that the market factor is correlated with other explanatory variables in our tests. However, the highest correlation between the market factor and another explanatory variable is only 0.24 (with consumption growth), so this seems unlikely. On the other hand, in the regressions without a constant, MKT is statistically significant. The fact that the sign of the risk premium for the MKT is negative is not easily interpretable as it is in contrast to theory, but Fama and French(1992) found a negative relation within the size decile on portfolios sorted on size and market betas.

The pricing errors are jointly not significantly different from zero in most of our regressions, which implies that our 4-factor model does a good job in pricing the assets. That is in stark contrast to the results from Carhart 4-factor model (lower section of table 4 and 5), where the pricing errors are jointly significantly different from zero.

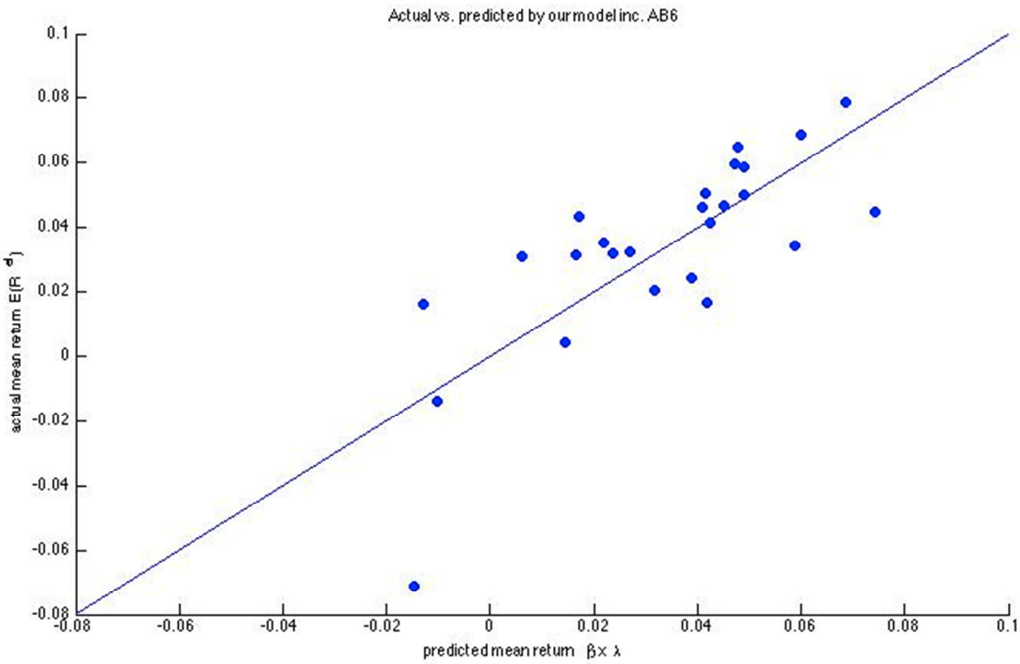
The lower sections of table 4 and 5 include additional factors downloaded from Kenneth French's website (the value factor HML, size factor SMB, and Momentum factor MOM). These factors are known to price assets, although they do not have a clear story motivated by theory (Cochrane , 2005a). If we compare the FF3 factor model (MKT, SMB and HML) and the Carhart 4-factor model (FF3 + MOM) to our 4-factor model including MKT, CON_g, CSI_g and GAR our model outperforms these models both in R^2 and RMSE. Section 4.7 further explores the impact of adding these additional factors as controls to our 4-factor model.

In table 10-13 in the appendix, the premium decompositions of each portfolio are reported for the model specifications with our most significant results. For our 4-factor model with our priced volatility factors (GAR, $AB6$), we see that the risk premium is higher for value stocks, which is consistent with the findings by Tedongap (2010), who showed that value stocks pay high average returns because they covary more negatively with innovations in consumption volatility than other stocks. We also note from the premium decomposition table that value stocks have a higher exposure to expected consumption growth, meaning that they covary more with innovations in expected consumption growth (than growth stocks). For size, there seems to be no apparent difference between smaller and larger stocks for neither exposure to expected consumption growth nor volatility.

Since we avoid constructing consumption dynamics when we capture expected consumption growth and volatility, we alleviate some of the errors in the estimate of these variables. On the other hand, we rely on the CSI as a proxy for investor's expected consumption dynamics. As long as the growth in the CSI accurately proxies the agent's (unknown) innovations about future consumption growth, we diminish the estimation bias by avoiding modelling expected consumption dynamics and allow for larger dispersion in expected consumption growth, compared to the highly persistent model dynamics in other papers (see Boguth & Kuehn, forthcoming; Lettau, Ludvigson, & Wachter, 2008). Another concern regarding the econometric inferences from our tests is that the betas in the first pass regression are estimates and thus measured with noise. The FM procedure does not correct for this, but we follow common practise in academia and only control for overlapping observations (heteroscedasticity and autocorrelation) in our explanatory variables as in Newey and West(1987). However, we correct for the estimation bias in the estimates of the χ^2statistics in the two-pass regression following Shanken(1992) as presented in the appendix.

4.6 Visual output

Figure 8- Actual vs. predicted, No constant



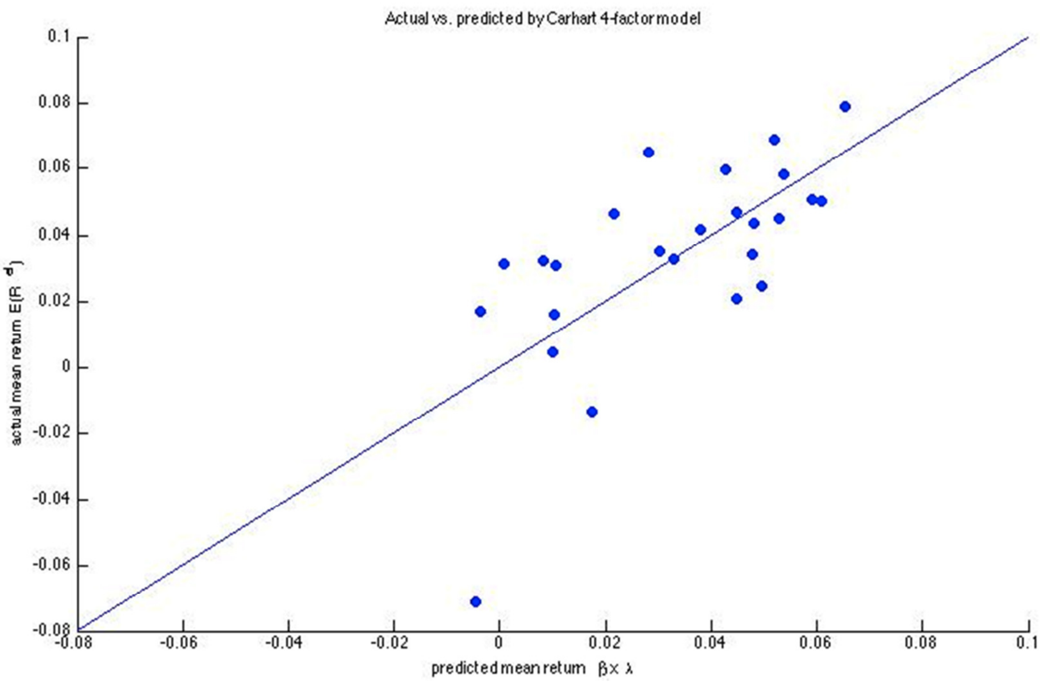
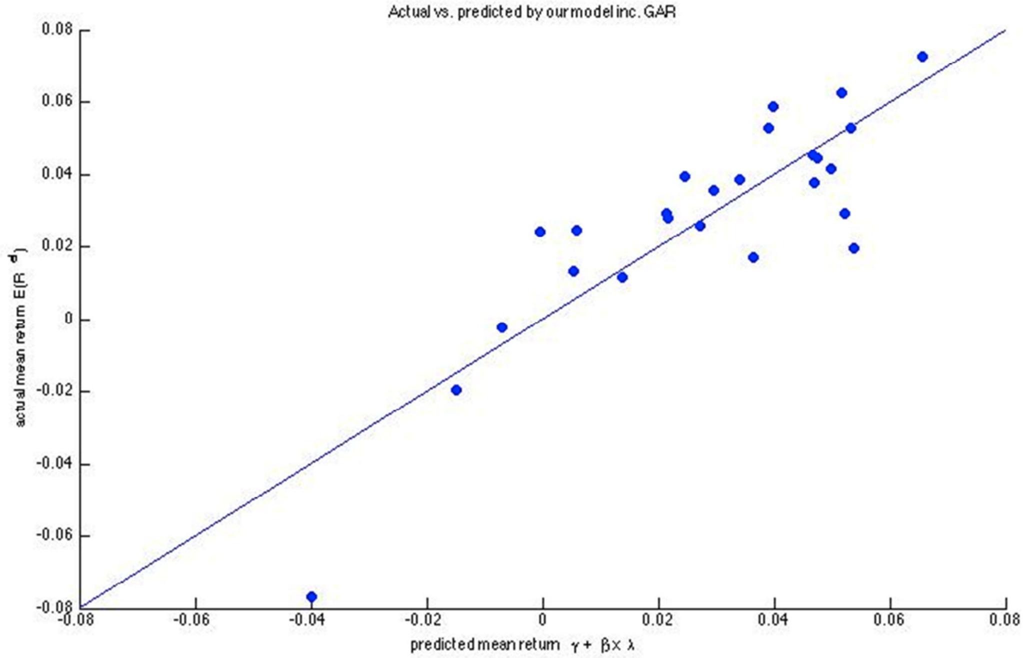
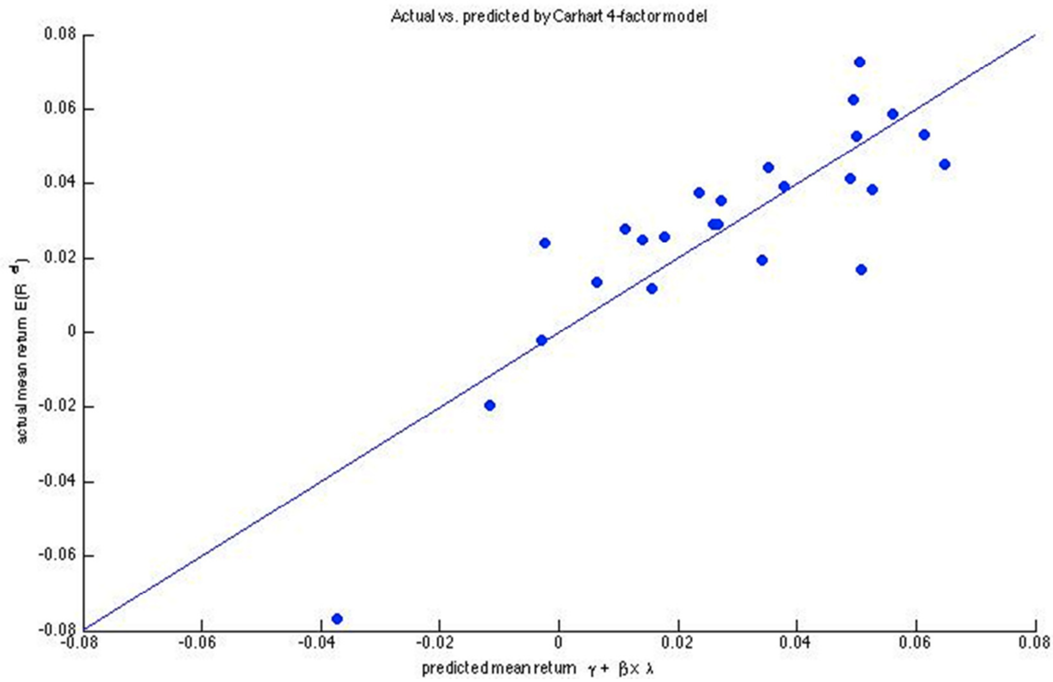


Figure 9- Actual vs. predicted, Free constant





Even though the pricing implication of our long-term factors is the main focus of this paper, it is interesting to see how well our factors price these portfolios. Especially our 4-factor model in the no intercept test with *AB6* as a measure of innovations in expected consumption volatility is doing a visually better job than the Carhart model in pricing the portfolios(this is also confirmed in the test result tables). In particular, the portfolios with high returns (value portfolios) are better priced by our model. The difference in pricing efficiency is not as striking in the regressions with a free constant, even though the ability of our model, with GAR as measure of growth in volatility, better price the value portfolios.

4.7 Including additional risk factors as controls

To further investigate the implications of our findings we include the factors HML to control for value, SMB to control for size, and MOM to control for momentum. Although these factors proxy for some unknown underlying risk (Cochrane, 2005a) and are unmotivated by the theory in this paper, it is still of interest to see how the estimates and significance of our factors change when we include these additional factors as regressors. All three factors are downloaded from Kenneth French website. Looking at the correlation matrix in appendix VI, we observe that none of the additional factors are materially correlated with any of our factors.

Table 6

Fama Macbeth including additional Factors

The sample period is 1979.03-2011.12. The additional factors are HML(Value), SMB(Size) and MOM(Momentum). In the upper section we test our model in a regression with no constant by adding additional factors. In the second part we do the reversed and add our factors to the Carhart 4-factor model. The bottom two parts are following the same logic but for regressions with a free constant. All estimates are multiplied from monthly to annual estimates and reported in %. All t-statistics are corrected for heteroskedasticity and autocorrelation using Newey-West standard errors with j-lags. Numbers in bold shows statistical significance at the 90%-level.

MKT	CONg	CSIg	GAR	AB3	AB6	BO3	BO6	HML	SMB	MOM	R^2	AdjR2	RMSE
Including additional factors in our 4-factor model (No Constant)													
MKT	*CONg*	*CSIg*	*GAR*										
0.03	0.27	4.40	-0.40								0.64	0.56	2.03
(0.13)	**(1.71)**	**(3.31)**	**(-2.39)**										
0.04	0.27	3.36	-0.23					0.08	0.27		0.64	0.52	1.93
(0.18)	**(3.38)**	**(2.73)**	**(-2.12)**					(0.47)	(1.08)				
0.03	0.35	1.44	-0.14					0.09	0.16	-1.81	0.66	0.52	1.89
(0.14)	**(4.84)**	(1.16)	(-1.44)					(0.56)	(0.67)	**(-2.13)**			
MKT	*CONg*	*CSIg*			*AB6*								
0.12	0.17	5.58			-4.01						0.64	0.57	1.92
(0.46)	(1.32)	**(3.07)**			**(-2.22)**								
0.08	0.25	3.86			-3.07			0.08	0.29		0.66	0.55	1.83
(0.34)	**(3.21)**	**(3.46)**			**(-2.82)**			(0.54)	(1.01)				
0.06	0.36	0.88			-3.31			0.08	0.12	-2.48	0.71	0.60	1.71
(0.23)	**(4.84)**	(0.72)			**(-2.96)**			(0.57)	(0.42)	**(-3.03)**			
Including selected factors in the Carhart 4-factor model (No Constant)													
MKT								*HML*	*SMB*	*MOM*			
0.08								0.13	0.53	-2.03	0.51	0.41	2.16
(0.33)								(0.87)	**(2.33)**	**(-2.61)**			
(0.07)		4.18						(0.14)	(0.52)	-1.02	0.57	0.45	2.10
(0.30)		**(3.55)**						(0.90)	**(2.29)**	(-1.18)			
(0.06)			-0.23					-0.10	0.50	-1.72	0.55	0.43	2.17
(0.25)			**(-2.43)**					(-0.66)	**(2.01)**	**(-2.20)**			
(0.09)					-3.75			0.12	0.48	-2.37	0.60	0.49	2.02
(0.39)					**(-3.38)**			(0.80)	**(1.71)**	**(-3.37)**			
(0.05)		4.35	-0.26					(0.11)	(0.48)	-0.61	0.60	0.47	2.04
(0.21)		**(3.66)**	**(-2.74)**					(0.68)	**(1.96)**	(-0.71)			
0.09		3.86			-3.53			0.12	0.48	-1.48	0.63	0.51	1.93
(0.36)		**(3.32)**			**(-3.13)**			(0.84)	(1.69)	**(-1.85)**			
Including additional factors in our 4-factor model (Free Constant)													
MKT	CONg	CSIg	GAR	AB3	AB6	BO3	BO6	HML	SMB	MOM	R^2	AdjR2	RMSE
MKT	*CONg*	*CSIg*	*GAR*										
-0.85	0.03	3.26	-0.29								0.72	0.67	1.54
(-1.67)	(0.27)	**(2.47)**	**(-2.24)**										
-2.22	0.00	2.70	-0.62					-0.05	-0.09		0.58	0.50	2.09
(-5.06)	(0.03)	**(2.20)**	**(-4.48)**					(-0.31)	(-0.35)				
-2.19	0.02	2.19	-0.59					-0.05	-0.11	-1.02	0.88	0.83	1.03
(-5.04)	(0.31)	**(1.79)**	**(-4.69)**					(-0.29)	(-0.45)	(-1.22)			
Including selected factors in the Carhart 4-factor model (Free Constant)													
MKT								*HML*	*SMB*	*MOM*			
-1.72								0.05	0.09	-2.43	0.71	0.66	1.57
(-4.80)								(0.32)	(0.43)	**(-3.13)**			
-1.64		2.35						0.06	0.11	-1.77	0.74	0.67	1.51
(-4.53)		**(1.93)**						(0.37)	(0.50)	**(-2.04)**			
-2.28			-0.58					-0.05	-0.12	-1.70	0.85	0.81	1.13
(-5.51)			**(-5.20)**					(-0.33)	(-0.51)	**(-2.17)**			
-2.20		2.22	-0.59					-0.05	-0.11	-1.00	0.88	0.84	1.03
(-5.27)		**(1.81)**	**(-5.24)**					-(0.29)	(-0.45)	(-1.18)			

Table 6 summarizes the findings of including the additional factors HML, SMB, and MOM in selected regressions of our 4-factor model that provided the strongest results in our previous section. The table also includes results where we start with the Carhart 4-factor model and add our factors to see the effect.

Starting by looking at the impact of including additional controls in the regressions without a constant we notice that CSI_g, GAR and $AB6$ all hold up well to the HML and SMB factors. They all remain significant and the estimates are only slightly lowered. CON_g even goes from insignificant to significant in the specification with $AB6$. R^2 is only marginally increased from the inclusion of the two additional factors, while RMSE is only marginally reduced. Neither HML nor SMB are significant when combined with our factors. Since SMB was significant in the test of the FF-3 factor model, this implies that our model drives out the SMB factor.

Innovations in expected consumption growth (CSI_g) is priced even when we include HML and SMB and the economic significance is large at 3.38% (t-stat 3.46), Including MOM reduces the significance considerably for GAR and CSI_g, but $AB6$ and CON_g remains strongly significant even after the inclusion of all Carhart factors. The coefficient for $AB6$ is large at -3.31% and highly significant (t-stat -2.96) which is a sign that this factor has explanatory power beyond all the Carhart factors. MOM is significant in both specifications suggesting that it has explanatory power in addition to what our 4-factors provide. CON_g is also highly statistical significant but the economic significance is low at 0,36% annually (t-stat 4.84).

If we look at the section underneath (section two, no intercept) where we do the reversed and include our factors into the Carhart 4-factor model it is noticeable that all of our factors derived from the CSI remain significant through most of the tests. CSI_g is highly significant and the economic magnitude is large. It seems like that factor is driving out the MOM factor as MOM loses its significance and the estimate is halved when CSI_g is included. $AB6$ and GAR do not seem to drive out any of the Carhart factors, but adds some explanatory power to the model.

Looking at the results with a free intercept, it is striking to see that our model specification including GAR almost completely sustains its economic and statistical significance when including the momentum factor (HML and SMB was not priced in the FF-3 or Carhart model in the tests with a free intercept, so we did not anticipate much effect of including them). The estimates of CSI_g and GAR factors are of expected signs and highly significant.

In the lower part of the table we investigate how the Carhart model hold up against the inclusion of our factors in the tests with a free intercept. It seems like MOM holds up against CSI_g and GAR separately, even though the coefficient and the significance decreases. However, when both of our factors are combined they drive out MOM.

4.8 Fama-Macbeth procedure on other test assets

Acknowledging the critique by (Lewellen, Nagel, & Shanken, 2010), where they highlight potential issues with the usage of the 25 size and book-to-market sorted portfolios as test assets, we also test our factors on the 25 short-term reversal and size portfolios, and the 25 long-term reversal and size portfolios separately. The results from these tests are presented in appendix VIII.

The "return reversal" is an established phenomenon in stock markets. What this implies is that assets that have had high returns over the prior period tend to see lower returns in the future. Two possible explanations for its existence have been discussed in academia. The first, suggested by Shiller(1984), Black(1986) and Stiglitz(1989), is that return reversal is a result of investor overreaction to information. The second, suggested by Grossman & Miller(1988) and Jegadeesh & Titman (1995), is grounded in liquidity and due to the price pressure that can occur when the short-term demand curve of a stock is downward sloping or the supply curve is upward sloping.

Looking first at the tests using the short-term reversal portfolios in table 16 and table 17, we see that $BO3$, $B06$, $AB3$ and $AB6$ are all highly significant in univariate regressions with a free constant. The signs are negative as expected and the economic magnitude is large, ranging between -3.98% to -6.20% on annual basis. The CSI_g is significant through all specifications of our 4-factor model, both in tests with and without a constant. The economic significance in these estimates is even larger than for our main test assets of this paper (the size and book-to-market sorted portfolios). The estimates are ranging between 4.51% and 8.83%. When it comes to the different specification of the volatility factor in our 4-factor model, GAR do not add any value to the regressions, as it remains insignificant in all regressions. However, $BO3$ and $AB3$ are both highly significant and large in economic magnitude, although the estimates drop from the univariate estimates to -2.46% from -4.39%. When it comes to the explanatory power the 4-factor specification with $AB3$ is the one that performs the best. It does a better job in pricing the portfolios than the Carhart factors. This is consistent both for the regression with and without a free constant.

Table 18 and table 19 shows results from the tests using portfolios sorted on long-term reversal and size as test assets. There are many surprising results here. Firstly, all of our factors are significant when tested in a univariate regression without a constant. Second, none of the Carhart factors are significant. Third, in the specification including $AB3$ as a volatility measure, both CSI_g and $AB3$ are significant, further validating our model. Compared to the results from the regressions using the value and size portfolios as test assets, the MKT factor is positive and significant in many regressions which is in line with the general theory of the market beta.

Notable is also that CON_g is significant only in the univariate regression, but as we include other factors, consumption growth comes out insignificant.

All significant factors in the regressions on both long-term and short-term reversal portfolios are of the expected sign, and generally the insignificant coefficients are also of the correct signs. In general, the results from the regressions on the additional test assets sorted on return reversal and size suggest that innovations in expected consumption growth and volatility are priced in the cross-section, even though the results are quite varying between different specifications.

5. Conclusion

In this paper, we started out by presenting the Long-Run Risks framework and the intuition behind using the University of Michigan's Consumer Sentiment Index to capture innovations in expected consumption growth and volatility. Rather than constructing a model based on a stochastic process using historical data for capturing innovations in expected consumption growth as in past literature, we capture these innovations through a forward-looking variable, thus allowing for greater dispersion in expectations. We construct a four-factor model including the market return, consumption growth, innovations in expected consumption growth (proxied by CSI growth) and innovations in the volatility of expected consumption growth (proxied by various measures of volatility in CSI growth). We then tested the pricing implications of the model on the 25 size and book-to-market, the 25 short-term and reversal, and on the 25 long-term and reversal portfolios respectively.

Our findings imply that innovations in expected consumption growth and innovation in expected consumption volatility are important risk factors for understanding the cross-section of asset returns. The results with regard to our proxy of the change in beliefs about expected consumption growth (CSI_g) is priced in almost all regressions with our 4-factor model, with the exception being the pricing of the tests using the portfolios sorted on long-term reversal and size. Although innovations in expected consumption growth is not significantly priced in all our specifications, the results are all pointing in the same direction and thus confirms its pricing implications in the Long-Run Risk framework. In line with theory, the risk premia of innovations in expected consumption growth is positive, meaning that investors require a risk premium to hold assets that covary positively with innovations in expected consumption growth, since these assets pay off poorly when the expected outlook of future consumption growth drops (expected "bad times").

The price of risk for innovations in the volatility of expected consumption growth (GAR, AB, BO) is consistently negative and significant in many of our tests. Investors require a risk premia to hold assets with payoffs that covary negatively with growth in economic uncertainty, which is consistent with the general findings in the Long-Run Risk Literature (Ang, Hodrick, Zhang, & Xing, 2006; Boguth & Kuehn, forthcoming; Tédongap, 2010).

Although the main focus of this paper is the pricing implications of innovations in expected consumption growth and volatility, it is interesting to reflect on the superior pricing power of our 4-factor model compared to the Carhart 4-factor model. The stronger performance of our model is consistent on all three sets of test assets,

The true purpose of this paper was to follow the call from Cochrane (2005a), to connect asset returns to macroeconomic events. In the light of this exploration, it is important to have in mind that our results rely on the "story of our proxy" to capture innovations in expected consumption growth and volatility. Still, we believe that this study shows that using a proxy (CSI) is an interesting addition to the Long-Run Risks literature, since it enables us to capture larger dispersions in innovations compared to past research that model the dynamics of expected consumption growth.

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Appendix

I. CSI survey questions

The following questions comprise the survey:

Present conditions question

Question 1) *Do you think now is a good or bad time for people to buy major household items?* [good time to buy/uncertain, depends/bad time to buy]

Question 2) *Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?* [better/same/worse]

Expectations questions

Question 3) *Now turning tot business conditions in the country as a whole- do you think that during the next twelve months, we'll have good times financially or bad times or what?* [good times/uncertain/bad times]

Question 4) *Looking ahead, which would you say is more likely- that in the country as a whole we'll have continuous good times during the next five years or so or that we'll have periods of widespread unemployment or depression, or what?* [good times/uncertain/bad times]

Question 5) *Now looking ahead- do you think that a year from now, you (and your family living there) will be better of financially, or worse off, or just about the same as now?* [better/same/worse]

II. Time series plots of original data series

Figure 10.

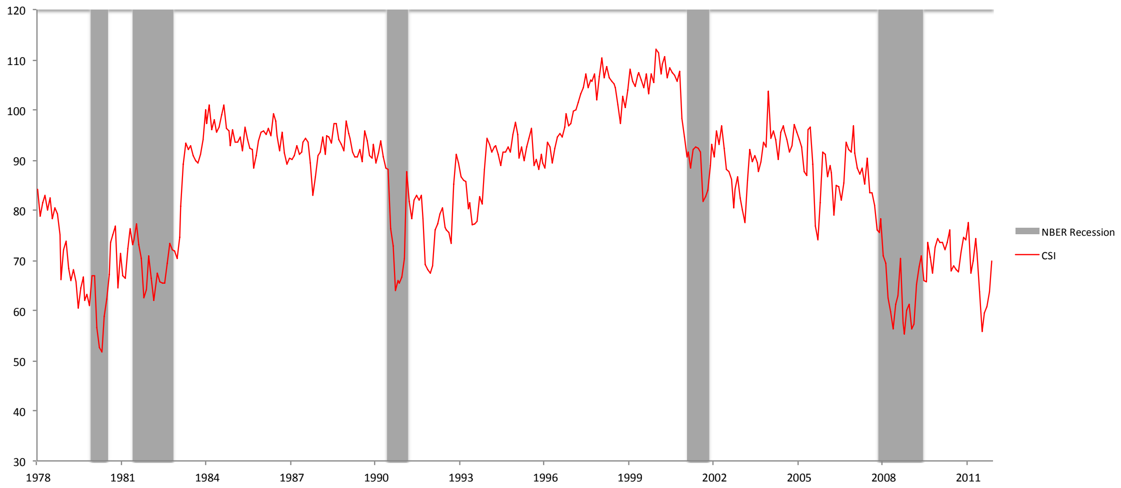


Figure 11.

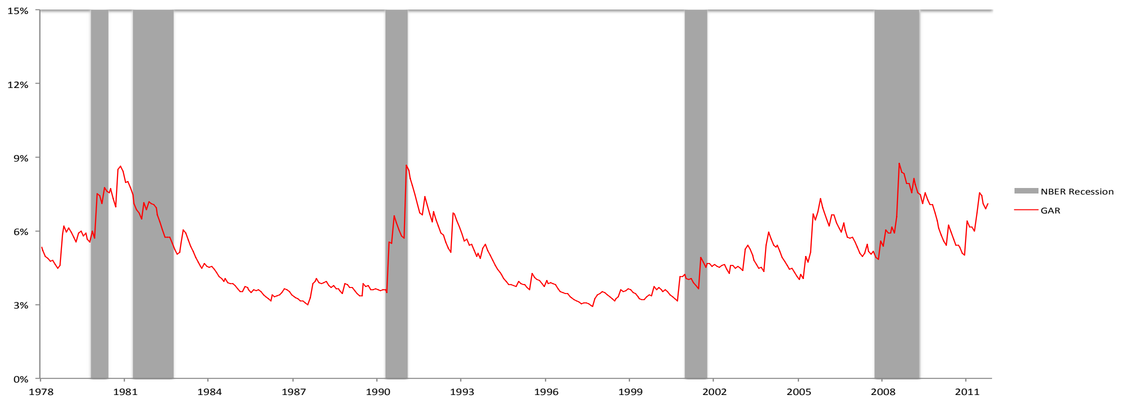


Figure 12.

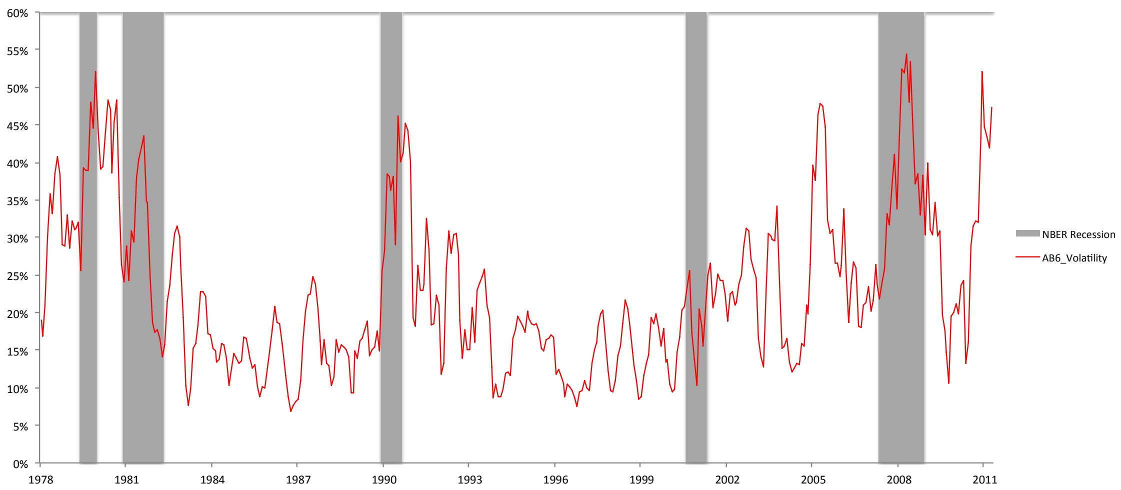
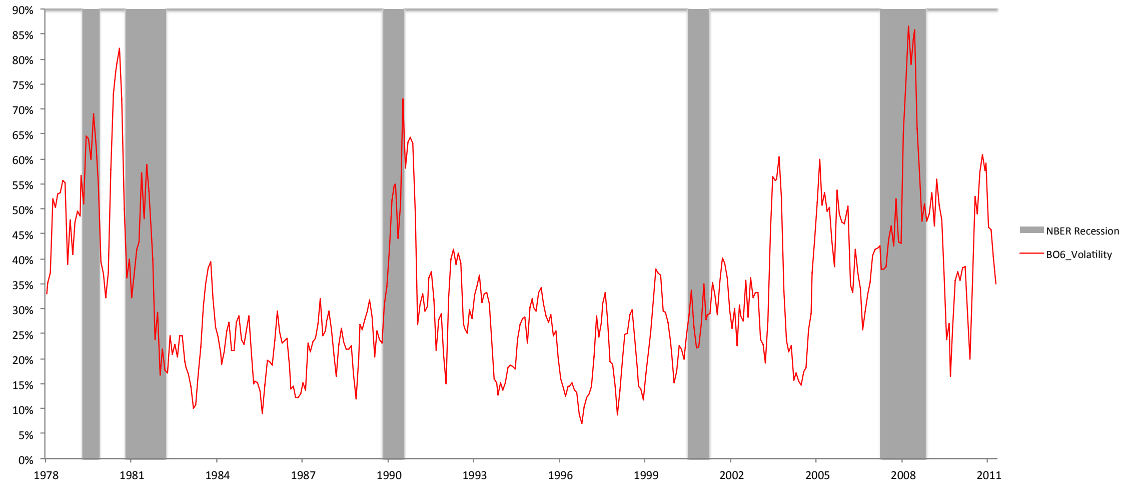


Figure 13.



III. Summary statistics of test-assets

Table 7

Summary Statistics for FF-Portfolios: Book-To-Market (BE/ME) Quintiles

This table presents summary statistics of means and standard deviations for the 25 Fama-French size-value sorted portfolios. The sample period is 1979.3-2011.12.

Size	Low	2	3	4	High	Low	2	3	4	High
					Real Excess Returns					
			Mean					Standard Deviation		
Small	-0.498	0.308	0.417	0.561	0.625	8.221	6.920	5.891	5.489	6.005
2	-0.061	0.301	0.504	0.510	0.442	7.480	6.082	5.473	5.349	6.122
3	0.057	0.354	0.394	0.412	0.658	6.914	5.661	5.118	5.015	5.534
4	0.258	0.250	0.275	0.348	0.367	6.153	5.416	5.378	4.851	5.423
Big	0.141	0.253	0.136	0.164	0.202	4.881	4.755	4.681	4.509	5.206

Table 8.

Summary Statistics for 25 short-term reversal and size portfolios

This table presents summary statistics of means and standard deviations for the 25 short-term reversal and size portfolios collected from Kennet French's website. The sample period is 1979.3-2011.12. All returns are Real excess returns.

Size	Low	2	3	4	High	Low	2	3	4	High
					Real Excess Returns					
			Mean					Standard Deviation		
Small	0.485	0.298	0.389	0.378	-0.100	7.919	5.886	5.445	5.359	6.589
2	0.674	0.787	0.554	0.399	0.179	7.888	5.971	5.499	5.438	6.663
3	0.646	0.666	0.564	0.448	0.113	7.526	5.547	5.207	5.048	6.175
4	0.494	0.737	0.483	0.385	0.107	7.293	5.496	4.831	4.884	5.875
Big	0.189	0.380	0.308	0.299	0.074	6.396	4.924	4.429	4.450	5.223

Table 9.

Summary Statistics for 25 long-term reversal and size portfolios

This table presents summary statistics of means and standard deviations for the 25 long-term reversal and size portfolios collected from Kennet French's website. The sample period is 1979.3-2011.12. All returns are real excess returns.

Size	Low	2	3	4	High	Low	2	3	4	High
					Real Excess Returns					
			Mean					Standard Deviation		
Small	0.592	0.491	0.587	0.520	0.245	7.065	5.504	5.160	5.301	6.153
2	0.718	0.546	0.734	0.639	0.433	7.188	5.675	5.123	5.157	6.412
3	0.664	0.641	0.578	0.459	0.452	6.541	5.115	4.763	4.973	6.192
4	0.507	0.436	0.524	0.486	0.425	6.004	5.072	4.702	4.838	6.130
Big	0.621	0.417	0.361	0.311	0.295	5.879	4.627	4.367	4.618	5.537

IV. Two-pass cross sectional approach to calculate standard errors

Cochrane (2005b) presents the following methodology for correcting both for estimation bias and correlated errors terms. The major difference between the FM Procedure and the two-pass approach is that the factor risk premia λ in the FM approach is estimated from a regression across assets of *average* returns on the betas estimated in the first- regression. The first step is similar as in the Fama-Macbeth procedure where the risk exposures are estimated in a time-series regression.

The second step in the two-pass approach is:

$$E(R_i^e) = \hat{\beta}_{i,f^1}\lambda_{1,} + \cdots + \hat{\beta}_{i,f^K}\lambda_K + \alpha_i$$

For the case of no intercept the cross-sectional estimates are calculated as:

$$\hat{\lambda} = \left(\beta' \beta\right)^{-1} \beta' E_T(R^e)$$

$$\hat{\alpha} = E_T(R^e) - \hat{\lambda}\beta$$

Where vectors from 1 to N are of the form $= [\beta_1\, \beta_2 \dots \beta_N\,]'$, and similarly for R_t^e and α.

For the case of a free intercept the only difference is $\beta = \begin{bmatrix} 1 & 1 \cdots 1 \\ \beta_1 & \beta_2 \cdots \beta_N \end{bmatrix}'$

The correct asymptotic standard errors from the model without a constant are calculated as:

$$\sigma^2(\hat{\lambda}) = \frac{1}{T}\left[\left(\beta' \beta\right)^{-1} \beta' \,\Sigma \beta \left(\beta' \beta\right)^{-1} \left(1 + \lambda' \,\Sigma_f^{-1} \lambda\right) + \Sigma_f\right]$$

Here Σ_f is the variance-covariance matrix of the factors and $\Sigma = \mathrm{cov}\left(\varepsilon_t, \varepsilon_t'\right)$ for the residuals from the time series regression.

For the model with a free constant the asymptotic standard errors are calculated as:

$$\sigma^2\begin{pmatrix}\hat{\gamma} \\ \hat{\lambda}\end{pmatrix} = \frac{1}{T}\left[\left(\beta' \beta\right)^{-1} \beta' \,\Sigma \beta \left(\beta' \beta\right)^{-1} \left(1 + \lambda' \,\Sigma_f^{-1} \lambda\right) + \begin{bmatrix} 0 & 0 \\ 0 & \Sigma_f \end{bmatrix}\right]$$

The asymptotic variance-covariance matrix of the pricing errors is:

$$cov(\alpha) = \frac{1}{T}\left[(I_N - \beta\left(\beta' \beta\right)^{-1} \beta' \,)\,\Sigma \left(I_N - \beta\left(\beta' \beta\right)^{-1} \beta' \right)\left(1 + \lambda' \,\Sigma_f^{-1} \lambda\right)\right]$$

This is the variance-covariance matrix we use to calculate the X^2 presented in our tables of results.

V. Premium decompositions

Table 10.

Fama-Macbeth no constant

The premium decomposition of each portfolio is presented in this table. From the left is the observed return of the portfolio, the return predicted by our model, the absolute pricing error of the portfolio, followed by the premium contribution of each factor $\beta^f * \lambda^f$ for every portfolio respectively. The numbers are presented on an annual basis.

		Actual Return	Predicted Return	Absolute pricing errors	MKT	CONg	CSIg	GAR
Small	Low	-7.1%	-2.2%	4.9%	0.6%	-2.6%	0.1%	-0.2%
	2	3.1%	0.5%	2.6%	0.5%	-2.7%	1.0%	1.7%
	3	4.6%	3.7%	0.9%	0.4%	0.3%	1.5%	1.5%
	4	6.5%	2.8%	3.7%	0.4%	-0.7%	2.9%	0.3%
	High	6.9%	6.3%	0.6%	0.4%	-0.3%	3.0%	3.2%
2	Low	-1.4%	1.7%	3.1%	0.5%	-1.7%	1.3%	1.6%
	2	3.5%	3.1%	0.4%	0.4%	-1.0%	2.2%	1.5%
	3	6.0%	4.6%	1.4%	0.4%	0.0%	2.5%	1.6%
	4	5.8%	6.1%	0.2%	0.4%	0.2%	2.4%	3.1%
	High	5.0%	6.0%	1.0%	0.4%	-0.7%	3.7%	2.6%
3	Low	0.4%	1.3%	0.9%	0.5%	-1.4%	1.4%	0.8%
	2	4.2%	3.8%	0.4%	0.4%	-0.8%	2.3%	1.9%
	3	4.7%	4.5%	0.2%	0.4%	-0.8%	3.2%	1.7%
	4	5.1%	2.9%	2.1%	0.4%	-1.4%	2.3%	1.7%
	High	7.9%	7.3%	0.6%	0.4%	-0.6%	3.6%	4.0%
4	Low	3.1%	2.4%	0.8%	0.5%	0.4%	0.6%	0.8%
	2	3.2%	3.4%	0.2%	0.4%	-0.4%	1.0%	2.4%
	3	3.4%	6.6%	3.2%	0.4%	0.0%	2.7%	3.5%
	4	4.3%	1.2%	3.1%	0.4%	-1.1%	1.0%	0.9%
	High	4.5%	5.0%	0.5%	0.4%	0.0%	2.2%	2.4%
Big	Low	1.7%	1.7%	0.0%	0.4%	1.7%	1.3%	-1.7%
	2	3.2%	2.3%	0.9%	0.4%	1.1%	-0.1%	0.9%
	3	1.6%	-0.7%	2.3%	0.4%	0.4%	-2.4%	0.9%
	4	2.1%	1.1%	1.0%	0.3%	-0.4%	0.6%	0.6%
	High	2.4%	5.7%	3.3%	0.3%	1.4%	2.5%	1.5%
Average		**3.39%**		**1.53%**	**0.41%**	**-0.45%**	**1.71%**	**1.58%**

Table 11.

Fama-Macbeth no constant

The premium decomposition of each portfolio is presented in this table. From the left is the observed return of the portfolio, the return predicted by our model, the absolute pricing error of the portfolio, followed by the premium contribution of each factor $\beta^f * \lambda^f$ for every portfolio respectively. The numbers are presented on an annual basis.

		Actual Return	Predicted Return	Absolute pricing errors	MKT	CONg	CSIg	AB6
Small	Low	-7.1%	-1.5%	5.6%	2.0%	-1.7%	0.2%	-1.9%
	2	3.1%	0.6%	2.5%	1.7%	-1.7%	1.3%	-0.7%
	3	4.6%	4.1%	0.5%	1.4%	0.2%	1.9%	0.6%
	4	6.5%	4.8%	1.7%	1.3%	-0.5%	3.6%	0.3%
	High	6.9%	6.0%	0.9%	1.4%	-0.1%	3.8%	0.9%
2	Low	-1.4%	-1.0%	0.4%	1.9%	-1.1%	1.8%	-3.7%
	2	3.5%	2.2%	1.3%	1.6%	-0.6%	2.8%	-1.6%
	3	6.0%	4.7%	1.2%	1.4%	0.1%	3.2%	0.0%
	4	5.8%	4.9%	0.9%	1.3%	0.2%	3.0%	0.3%
	High	5.0%	4.9%	0.1%	1.5%	-0.4%	4.8%	-1.0%
3	Low	0.4%	1.5%	1.0%	1.8%	-0.9%	1.9%	-1.4%
	2	4.2%	4.3%	0.1%	1.5%	-0.5%	2.9%	0.3%
	3	4.7%	4.5%	0.2%	1.3%	-0.4%	4.0%	-0.4%
	4	5.1%	4.1%	0.9%	1.3%	-0.8%	2.9%	0.8%
	High	7.9%	6.9%	1.0%	1.3%	-0.3%	4.6%	1.2%
4	Low	3.1%	1.7%	1.5%	1.7%	0.3%	0.9%	-1.2%
	2	3.2%	2.7%	0.5%	1.5%	-0.2%	1.3%	0.1%
	3	3.4%	5.9%	2.5%	1.4%	0.1%	3.5%	0.9%
	4	4.3%	1.7%	2.6%	1.3%	-0.7%	1.4%	-0.2%
	High	4.5%	7.4%	2.9%	1.3%	0.1%	2.6%	3.3%
Big	Low	1.7%	4.2%	2.5%	1.4%	1.0%	1.7%	0.1%
	2	3.2%	2.4%	0.9%	1.3%	0.7%	-0.1%	0.4%
	3	1.6%	-1.3%	2.9%	1.3%	0.3%	-3.0%	0.2%
	4	2.1%	3.2%	1.1%	1.1%	-0.2%	0.7%	1.6%
	High	2.4%	3.9%	1.5%	1.2%	1.0%	3.3%	-1.5%
Average		**3.39%**		**1.49%**	**1.46%**	**-0.24%**	**2.20%**	**-0.10%**

Table 12.

Fama-Macbeth free constant

The premium decomposition of each portfolio is presented in this table. From the left is the observed return of the portfolio, the return predicted by our model, the absolute pricing error of the portfolio, the estimated intercept from the cross sectional regression, followed by the premium contribution of each factor $\beta^f * \lambda^f$ for every portfolio respectively. The numbers are presented on an annual basis.

		Actual Return	Predicted Return	Absolute pricing errors	Intercept	MKT	CONg	CSIg	GAR
Small	Low	-7.1%	-3.4%	3.7%	11.8%	-14.7%	-0.3%	0.0%	-0.2%
	2	3.1%	1.3%	1.8%	11.8%	-12.2%	-0.3%	0.7%	1.2%
	3	4.6%	3.5%	1.1%	11.8%	-10.5%	0.0%	1.1%	1.1%
	4	6.5%	4.5%	2.0%	11.8%	-9.5%	-0.1%	2.1%	0.2%
	High	6.9%	6.0%	0.9%	11.8%	-10.3%	0.0%	2.2%	2.3%
2	Low	-1.4%	-0.6%	0.7%	11.8%	-14.3%	-0.2%	0.9%	1.2%
	2	3.5%	2.7%	0.8%	11.8%	-11.6%	-0.1%	1.6%	1.1%
	3	6.0%	4.6%	1.4%	11.8%	-10.2%	0.0%	1.9%	1.2%
	4	5.8%	6.0%	0.1%	11.8%	-9.8%	0.0%	1.8%	2.2%
	High	5.0%	5.5%	0.4%	11.8%	-10.8%	-0.1%	2.7%	1.9%
3	Low	0.4%	-0.3%	0.7%	11.8%	-13.5%	-0.2%	1.1%	0.6%
	2	4.2%	3.5%	0.6%	11.8%	-11.2%	-0.1%	1.7%	1.4%
	3	4.7%	5.4%	0.7%	11.8%	-9.9%	-0.1%	2.3%	1.2%
	4	5.1%	5.0%	0.0%	11.8%	-9.5%	-0.2%	1.7%	1.2%
	High	7.9%	7.4%	0.5%	11.8%	-9.8%	-0.1%	2.7%	2.8%
4	Low	3.1%	0.4%	2.8%	11.8%	-12.5%	0.0%	0.5%	0.6%
	2	3.2%	3.1%	0.1%	11.8%	-11.1%	0.0%	0.8%	1.7%
	3	3.4%	5.8%	2.4%	11.8%	-10.5%	0.0%	2.0%	2.5%
	4	4.3%	3.7%	0.7%	11.8%	-9.4%	-0.1%	0.8%	0.7%
	High	4.5%	5.2%	0.7%	11.8%	-9.9%	0.0%	1.6%	1.7%
Big	Low	1.7%	1.6%	0.1%	11.8%	-10.1%	0.2%	1.0%	-1.2%
	2	3.2%	2.7%	0.5%	11.8%	-9.8%	0.1%	-0.1%	0.7%
	3	1.6%	1.2%	0.4%	11.8%	-9.5%	0.0%	-1.8%	0.7%
	4	2.1%	4.2%	2.1%	11.8%	-8.4%	0.0%	0.4%	0.4%
	High	2.4%	5.9%	3.5%	11.8%	-8.9%	0.2%	1.8%	1.1%
Average		**3.39%**		**1.16%**		**-10.72%**	**-0.05%**	**1.27%**	**1.13%**

Table 13.

Fama-Macbeth free constant

The premium decomposition of each portfolio is presented in this table. From the left is the observed return of the portfolio, the return predicted by our model, the absolute pricing error of the portfolio, the estimated intercept from the cross sectional regression, followed by the premium contribution of each factor βf*λf for every portfolio respectively. The numbers are presented on an annual basis.

		Actual Return	Predicted Return	Absolute pricing errors	Intercept	**MKT**	**CONg**	**CSIg**	**AB6**
Small	Low	-7.1%	-2.5%	4.6%	10.4%	-12.1%	-0.2%	0.1%	-0.8%
	2	3.1%	1.0%	2.0%	10.4%	-10.0%	-0.2%	1.1%	-0.3%
	3	4.6%	3.6%	1.0%	10.4%	-8.6%	0.0%	1.6%	0.2%
	4	6.5%	5.7%	0.7%	10.4%	-7.8%	-0.1%	3.0%	0.1%
	High	6.9%	5.5%	1.4%	10.4%	-8.5%	0.0%	3.2%	0.4%
2	Low	-1.4%	-1.5%	0.1%	10.4%	-11.8%	-0.1%	1.5%	-1.5%
	2	3.5%	2.5%	1.0%	10.4%	-9.6%	-0.1%	2.4%	-0.7%
	3	6.0%	4.7%	1.2%	10.4%	-8.4%	0.0%	2.7%	0.0%
	4	5.8%	5.1%	0.8%	10.4%	-8.1%	0.0%	2.6%	0.1%
	High	5.0%	5.1%	0.1%	10.4%	-8.9%	0.0%	4.0%	-0.4%
3	Low	0.4%	0.3%	0.2%	10.4%	-11.1%	-0.1%	1.6%	-0.6%
	2	4.2%	3.7%	0.5%	10.4%	-9.2%	-0.1%	2.5%	0.1%
	3	4.7%	5.5%	0.8%	10.4%	-8.1%	-0.1%	3.4%	-0.2%
	4	5.1%	5.3%	0.3%	10.4%	-7.8%	-0.1%	2.4%	0.3%
	High	7.9%	6.6%	1.3%	10.4%	-8.1%	0.0%	3.8%	0.5%
4	Low	3.1%	0.4%	2.7%	10.4%	-10.3%	0.0%	0.7%	-0.5%
	2	3.2%	2.4%	0.8%	10.4%	-9.1%	0.0%	1.1%	0.0%
	3	3.4%	5.0%	1.6%	10.4%	-8.7%	0.0%	2.9%	0.4%
	4	4.3%	3.6%	0.7%	10.4%	-7.7%	-0.1%	1.1%	-0.1%
	High	4.5%	5.9%	1.4%	10.4%	-8.1%	0.0%	2.2%	1.4%
Big	Low	1.7%	3.8%	2.1%	10.4%	-8.3%	0.1%	1.4%	0.0%
	2	3.2%	2.6%	0.6%	10.4%	-8.0%	0.1%	-0.1%	0.2%
	3	1.6%	0.2%	1.4%	10.4%	-7.8%	0.0%	-2.5%	0.1%
	4	2.1%	4.7%	2.7%	10.4%	-6.9%	0.0%	0.6%	0.7%
	High	2.4%	5.3%	2.9%	10.4%	-7.3%	0.1%	2.7%	-0.6%
Average		**3.39%**		**1.31%**		**-8.81%**	**-0.03%**	**1.85%**	**-0.04%**

VI. Correlation matrix between factors including HML, SMB and MOM

Table 14.

Correlation matrix between factors including HML, SMB and Momentum (MOM)

	MKT	**CONg**	**CSIg**	**AB3**	**AB6**	**BO3**	**BO6**	**GAR**	**SMB**	**HML**	**MOM**
MKT	100.00										
CONg	24.17	100.00									
CSIg	19.20	8.24	100.00								
AB3	-6.50	-5.08	1.31	100.00							
AB6	-4.45	-5.99	0.44	51.88	100.00						
BO3	-7.29	-8.55	0.25	53.00	27.01	100.00					
BO6	-8.63	-7.50	0.35	26.83	51.98	51.78	100.00				
GAR	-14.23	-4.76	-9.67	11.26	1.91	39.08	35.83	100.00			
SMB	**-17.24**	**0.55**	**-10.43**	**1.18**	**-4.02**	**0.01**	**-9.79**	**-1.52**	**100.00**		
HML	**27.51**	**12.35**	**0.11**	**-1.25**	**0.50**	**-5.37**	**-3.92**	**-5.10**	**-19.81**	**100.00**	
MOM	**5.73**	**-9.95**	**-0.63**	**3.21**	**4.41**	**0.46**	**2.11**	**3.98**	**-17.57**	**20.90**	**100.00**

VII. Summary statistics of control factors

Table 15.

The monthly factors are downloaded from Kenneth French website. HML is the value factor, SMB is size factor and MOM is the Momentum factor. The sample period is 1979.03-2011.12.

	Mean	SD	Skewness	Excess Kurtosis	Min	Max
SMB	0.21	2.92	0.39	2.26	-11.60	14.62
HML	0.22	3.58	-0.08	6.76	-20.79	19.72
MOM	1.25	4.57	1.60	9.63	-9.58	34.74

VIII. Additional test assets

Table 16.

Fama-Macbeth No constant

Short-term reversal and size portfolios

The sample period is 1979.03-2011.12. The test assets are downloaded from Kenneth French's website and are the 25 portfolios sorted on Short-term Reversal and Size. We calculate real excess returns and use non-overlapping returns for the portfolios. The number next to the AB and BO series denotes the J-th lags in the calculations. In the upper part, each factor is tested alone in the cross section. The second part tests show results of our model without the market factor. The third section comprises results from different specifications of our 4-factor model. The lower part includes estimates of the FF-3 and Carhart 4-factor model. All estimates and the Root Mean Square Errors(RMSE) are multiplied from monthly to annual estimates and reported in %. All t-statistics are corrected for heteroskedasticity and autocorrelation using Newey-West standard errors with j-lags. Numbers in bold shows statistical significance at the 90%-level.

MKT	CONg	CSIg	GAR	AB3	AB6	BO3	BO6	HML	SMB	MOM	R^2	AdjR2	RMSE
0.36											0.07	0.03	2.53
(1.47)													
	0.13										0.04	0.00	2.71
	(1.47)												
		1.50									0.13	0.09	2.31
		(1.50)											
			-0.20								0.07	0.03	2.52
			(-1.37)										
				-4.53							0.72	0.71	1.59
				(-1.60)									
					-6.23						1.01	1.01	2.30
					(-1.70)								
						-5.11					0.32	0.29	1.93
						(-1.48)							
							-3.79				0.31	0.28	2.09
							(-1.50)						
	-0.05	2.51	0.08								0.31	0.21	2.24
	(-0.51)	**(1.95)**	(0.53)										
	-0.02	0.65		-4.01							0.65	0.60	1.57
	(-0.30)	(0.46)		**(-2.79)**									
	-0.04	1.58			-3.29						0.51	0.44	1.86
	(-0.59)	(1.26)			**(-2.19)**								
	-0.06	0.70				-6.22					0.53	0.46	1.87
	(-0.73)	(0.48)				**(-3.06)**							
	0.00	-0.38					-5.81				0.45	0.37	2.06
	(-0.04)	(-0.16)					(-1.49)						
0.17	0.19	8.62									0.63	0.58	1.76
(0.69)	**(1.86)**	**(3.69)**											
0.17	0.18	8.53	-0.08								0.63	0.55	1.76
(0.65)	**(1.72)**	**(3.72)**	(-0.56)										
0.26	0.10	4.51		-3.08							0.74	0.69	1.43
(1.01)	(1.14)	**(2.69)**		**(-2.37)**									
0.23	0.12	6.51			-1.75						0.64	0.56	1.70
(0.89)	(1.51)	**(3.32)**			(-1.19)								
0.20	0.13	6.13				-4.39					0.70	0.64	1.60
(0.76)	(1.44)	**(2.65)**				**(-2.47)**							
0.20	0.19	6.54					-3.27				0.67	0.61	1.71
(0.82)	**(1.99)**	**(2.49)**					(-0.90)						
0.33								-0.14	1.15		0.34	0.24	2.00
(1.40)								(-0.87)	**(2.56)**				
0.30								0.01	0.40	-1.64	0.71	0.66	1.57
(1.27)								(0.08)	(1.05)	**(-2.30)**			

Table 17.

Fama-Macbeth Free constant
Short-term reversal and size portfolios

The sample period is 1979.03-2011.12. The test assets are downloaded from Kenneth French's website and are the 25 portfolios sorted on Short-term Reversal and Size. We calculate real excess returns and use non-overlapping returns for the portfolios. The number next to the AB and BO series denotes the J-th lags in the calculations. In the upper part, each factor is tested alone in the cross section. The second part tests show results of our model without the market factor. The third section comprises results from different specifications of our 4-factor model. The lower part includes estimates of the FF-3 and Carhart 4-factor model. All estimates and the Root Mean Square Errors(RMSE) are multiplied from monthly to annual estimates and reported in %. All t-statistics are corrected for heteroskedasticity and autocorrelation using Newey-West standard errors with j-lags. Numbers in bold shows statistical significance at the 90%-level.

MKT	CONg	CSIg	GAR	AB3	AB6	BO3	BO6	HML	SMB	MOM	R^2	AdjR^2	RMSE
0.35											0.07	0.03	2.53
(0.87)													
	-0.04										0.00	-0.04	2.62
	(0.40)												
		2.03									0.24	0.21	2.28
		(1.53)											
			-0.21								0.08	0.04	2.52
			(-1.02)										
				-4.26							0.63	0.62	1.58
				(-2.94)									
					-3.98						0.41	0.39	2.01
					(-2.64)								
						-6.20					0.47	0.45	1.91
						(-2.92)							
							-4.13				0.37	0.34	2.09
							(-2.25)						
	-0.10	2.44	0.12								0.28	0.18	2.22
	(-0.92)	**(1.85)**	(1.06)										
	-0.04	0.59		-4.00							0.64	0.59	1.57
	(-0.32)	(0.45)		**(-2.74)**									
	-0.06	1.51			-3.28						0.50	0.42	1.86
	(-0.53)	(1.30)			**(-2.13)**								
	-0.11	0.47				-6.28					0.50	0.43	1.85
	(-0.97)	(0.33)				**(-3.10)**							
	-0.10	-1.24					-6.74				0.42	0.33	2.00
	(-0.85)	(-0.55)					**(-1.74)**						
-0.27	0.09	8.83									0.60	0.54	1.67
(-0.71)	(0.81)	**(3.78)**											
-0.29	0.09	8.88	0.01								0.60	0.52	1.66
(-0.79)	(0.80)	**(3.90)**	(-0.12)										
-0.01	0.05	4.97		-2.86							0.72	0.66	1.40
(-0.02)	(0.48)	**(2.66)**		**(-2.02)**									
-0.16	0.07	7.46			-1.22						0.61	0.53	1.64
(-0.36)	(0.69)	**(2.99)**			(-0.71)								
-0.21	0.05	6.43				-4.24					0.67	0.60	1.51
(-0.59)	(0.39)	**(2.75)**				**(-2.40)**							
-0.34	0.07	6.02					-4.37				0.65	0.57	1.56
(-0.90)	(0.65)	**(2.43)**					(-1.23)						
0.60								-0.15	1.20		0.45	0.37	1.94
(1.32)								(-0.89)	**(2.45)**				
-0.15								0.09	0.01	-2.17	0.69	0.62	1.47
(-0.35)								(-0.54)	(0.03)	**(-3.49)**			

Table 18.

Fama-Macbeth No constant

25 portfolios sorted on Long-term reversal and Size

The sample period is 1979.03-2011.12. The test assets are downloaded from Kenneth French's website and are the 25 portfolios sorted on Long-term Reversal and Size. We calculate real excess returns and use non-overlapping returns for the portfolios. The number next to the AB and BO series denotes the J-th lags in the calculations. In the upper part, each factor is tested alone in the cross section. The second part tests show results of our model without the market factor. The third section comprises results from different specifications of our 4-factor model. The lower part includes estimates of the FF-3 and Carhart 4-factor model. All estimates and the Root Mean Square Errors(RMSE) are multiplied from monthly to annual estimates and reported in %. All t-statistics are corrected for heteroskedasticity and autocorrelation using Newey-West standard errors with j-lags. Numbers in bold shows statistical significance at the 90%-level.

MKT	CONg	CSIg	GAR	AB3	AB6	BO3	BO6	HML	SMB	MOM	R^2	AdjR2	RMSE
0.48											0.24	0.21	1.63
(1.96)													
	0.18										0.31	0.28	1.95
	(1.97)												
		1.95									0.50	0.48	1.54
		(1.97)											
			-0.25								0.39	0.36	1.85
			(-1.82)										
				-5.88							0.84	0.83	1.53
				(-1.87)									
					-8.09						1.34	1.35	1.40
					(-2.00)								
						-5.91					1.15	1.16	1.92
						(-1.84)							
							-4.46				0.91	0.91	2.23
							(-1.87)						
	0.04	1.91	0.02								0.43	0.35	1.53
	(0.46)	(1.38)	(0.19)										
	0.02	0.99		-3.05							0.45	0.37	1.42
	(0.25)	(0.82)		**(-2.45)**									
	0.02	1.14			-4.65						0.54	0.48	1.12
	(0.21)	(1.01)			**(-2.57)**								
	0.03	1.71				-0.28					0.40	0.31	1.54
	(0.37)	(1.11)				(-0.15)							
	0.04	2.12					1.22				0.49	0.42	1.49
	(0.52)	(1.61)					(0.67)						
0.42	0.08	2.67									0.44	0.36	1.52
(1.75)	(0.59)	(1.66)											
0.42	0.08	2.68	0.01								0.45	0.35	1.52
(1.65)	(0.59)	(1.67)	(-0.04)										
0.40	0.17	3.18		-4.36							0.59	0.51	1.33
(1.59)	(1.10)	**(1.96)**		**(-2.65)**									
0.45	0.08	2.26			-4.72						0.60	0.52	1.09
(1.78)	(0.61)	(1.65)			**(-2.58)**								
0.42	0.08	2.62				-0.38					0.44	0.33	1.52
(1.64)	(0.60)	(1.59)				(-0.20)							
0.43	0.08	2.69					1.11				0.51	0.41	1.48
(1.74)	(0.56)	**(1.83)**					(0.62)						
0.38								0.02	0.58		0.38	0.29	1.33
(1.61)								(0.09)	(1.64)				
0.38								0.03	0.54	-0.48	0.40	0.28	1.32
(1.60)								(0.15)	(1.50)	(-0.66)			

Table 19.

Fama-Macbeth Free constant

25 portfolios sorted on Long-term reversal and Size

The sample period is 1979.03-2011.12. The test assets are downloaded from Kenneth French's website and are the 25 portfolios sorted on Long-term Reversal and Size. We calculate real excess returns and use non-overlapping returns for the portfolios. The number next to the AB and BO series denotes the J-th lags in the calculations. In the upper part, each factor is tested alone in the cross section. The second part tests show results of our model without the market factor. The third section comprises results from different specifications of our 4-factor model. The lower part includes estimates of the FF-3 and Carhart 4-factor model. All estimates and the Root Mean Square Errors(RMSE) are multiplied from monthly to annual estimates and reported in %. All t-statistics are corrected for heteroskedasticity and autocorrelation using Newey-West standard errors with j-lags. Numbers in bold shows statistical significance at the 90%-level.

MKT	CONg	CSIg	GAR	AB3	AB6	BO3	BO6	HML	SMB	MOM	R^2	AdjR2	RMSE
0.07											0.00	-0.04	1.50
(0.16)													
	-0.10										0.09	0.05	1.43
	(-0.91)												
		0.88									0.10	0.06	1.43
		(0.71)											
			0.04								0.01	-0.03	1.50
			(0.26)										
				-2.85							0.20	0.16	1.35
				(-1.26)									
					-4.55						0.42	0.40	1.15
					(-1.72)								
						-1.47					0.07	0.03	1.45
						(-0.80)							
							0.52				0.01	-0.03	1.50
							(0.32)						
	-0.10	1.13	0.13								0.27	0.17	1.29
	(-0.92)	(0.86)	(0.92)										
	-0.08	0.38		-2.12							0.27	0.16	1.29
	(-0.73)	(0.33)		(-1.67)									
	-0.02	0.91			-4.10						0.47	0.39	1.10
	(-0.17)	(0.79)			**(-1.90)**								
	-0.09	0.78				-0.04					0.20	0.09	1.35
	(-0.83)	(0.53)				(-0.02)							
	-0.09	1.14					1.62				0.30	0.20	1.26
	(-0.76)	(0.93)					(0.88)						
-0.18	-0.01	2.31									0.26	0.15	1.30
(-0.49)	(-0.06)	(1.47)											
-0.25	-0.03	2.31	0.11								0.31	0.17	1.25
(-0.65)	(-0.19)	(1.50)	(0.76)										
-0.09	0.07	2.78		-3.51							0.41	0.29	1.16
(-0.24)	(0.45)	**(1.78)**		**(-2.20)**									
0.22	0.05	2.19			-4.00						0.51	0.41	1.06
(0.51)	(0.34)	(1.61)			**(-1.86)**								
-0.18	-0.01	2.31				-0.18					0.26	0.11	1.30
(-0.47)	(-0.06)	(1.44)				(-0.10)							
-0.19	-0.02	2.32					1.40				0.34	0.20	1.23
(-0.49)	(-0.16)	(1.66)					(0.78)						
-0.06								0.07	0.27		0.30	0.19	1.27
(-0.13)								(0.42)	(0.59)				
-0.09								0.09	0.21	-0.48	0.40	0.28	1.32
(-0.20)								(0.51)	(0.43)	(-0.66)			